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Probabilistic Wind and Power Predictions and Wind Resource Assessment with an Analog Ensemble

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National Center for Atmospheric Research – Boulder, CO, USA

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- Vattenfall
- Vestas Wind Systems
- Xcel Energy

Outline

- Analog Ensemble (AnEn) basic idea
- AnEn for short-term (i.e., 0-48 h) weather predictions
- AnEn for short-term (i.e., 0-72 h) power predictions
- AnEn for long-term (i.e., multi-year) wind resource assessment
- Summary and future work

- **Analog Ensemble (AnEn) basic idea**
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Weather analogs: basic idea

Weather analogs: basic idea



Today

Weather analogs: basic idea



Today



One week ago?

Weather analogs: basic idea



Today



One week ago?

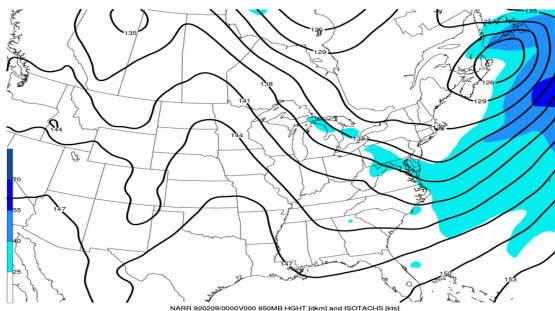


5 years ago?!?

Weather analogs: basic idea



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Today



One week ago?

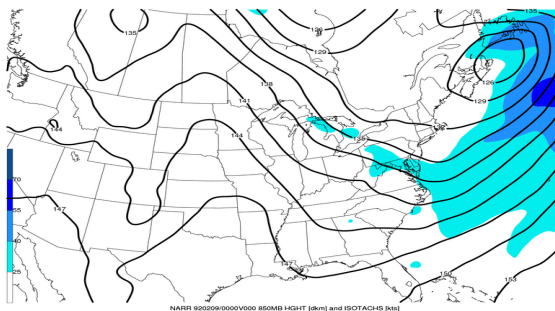


5 years ago?!?

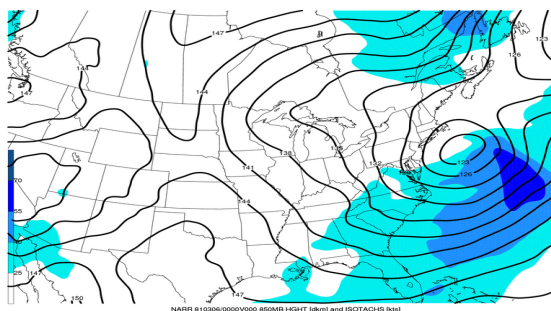
Weather analogs: basic idea



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Today



One week ago?

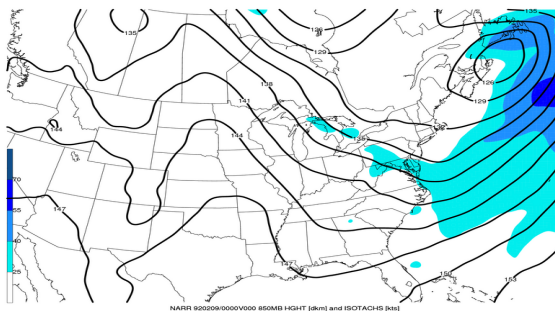


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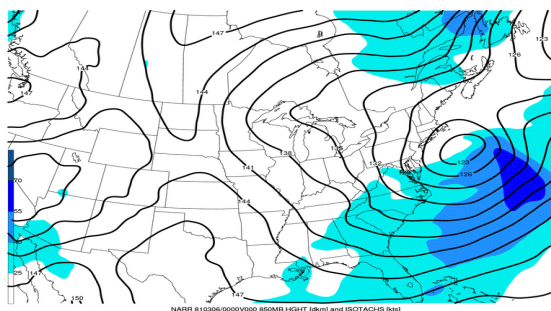
Weather analogs: basic idea



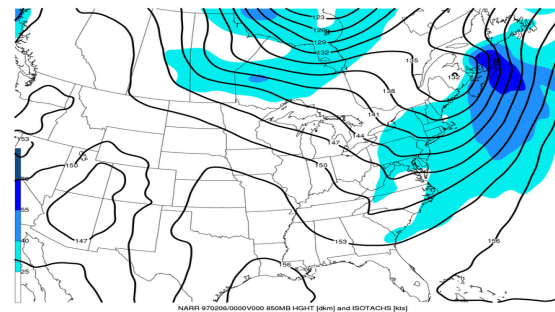
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Today



One week ago?

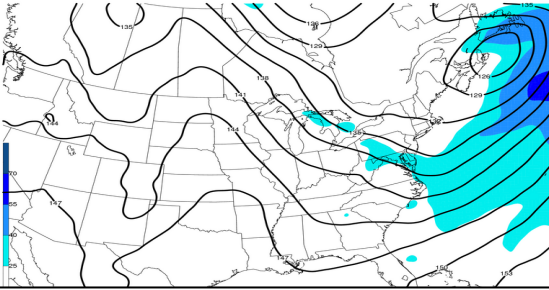


5 years ago?!?

Weather analogs: basic idea



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Can we use this information
(i.e., both obs and re-analysis),
to improve forecasts or resource estimates?



5 years ago?!?

There is a problem...

Edward Lorenz, “Atmospheric predictability as revealed by naturally occurring analogues” (JAS 1969):

...

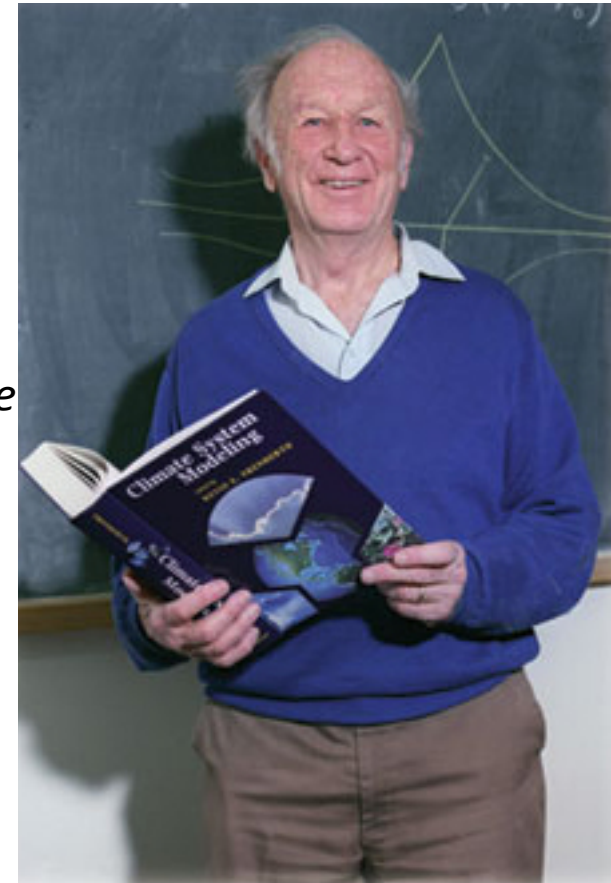
Five years of twice-daily height values of the 200-, 500-, and 850-mb surfaces at a grid of 1003 points over the Northern Hemisphere

...

There are numerous mediocre analogues but no truly good ones.

...

The likelihood of encountering any truly good analogues by processing all existing upper-level data appears to be small.



A possible solution?



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Huug van den Dool, “Searching for analogues, how long must we wait?” (Tellus 1994):

...

It is found that it would take a library of order of 10^{30} years to find 2 observed flows that match to within current observational error over a large area such as the Northern Hemisphere.

...

Obviously, with 10-100 years of data, the probability of finding natural analogous is very small, unless one is satisfied with analogy over small areas or in just 2 or 3 degrees of freedom



Outline

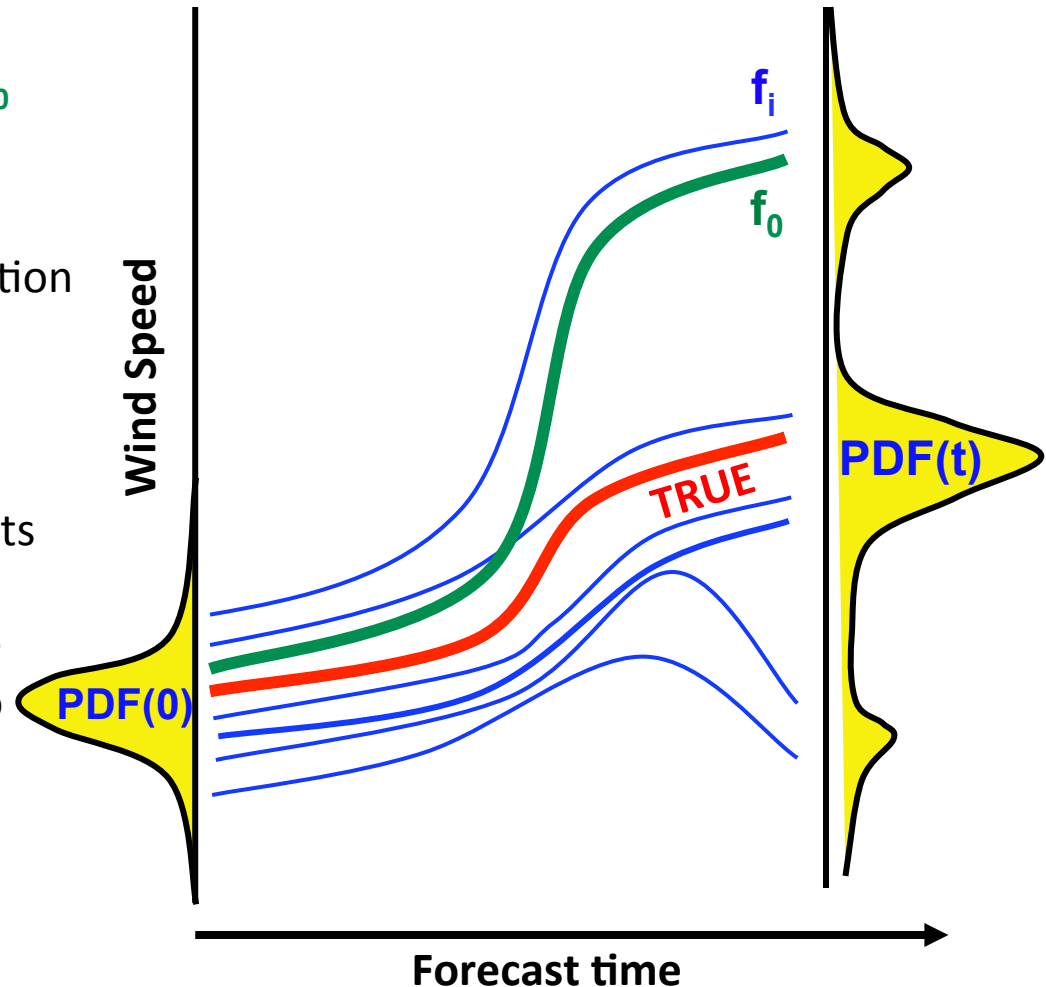
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Ensemble Prediction

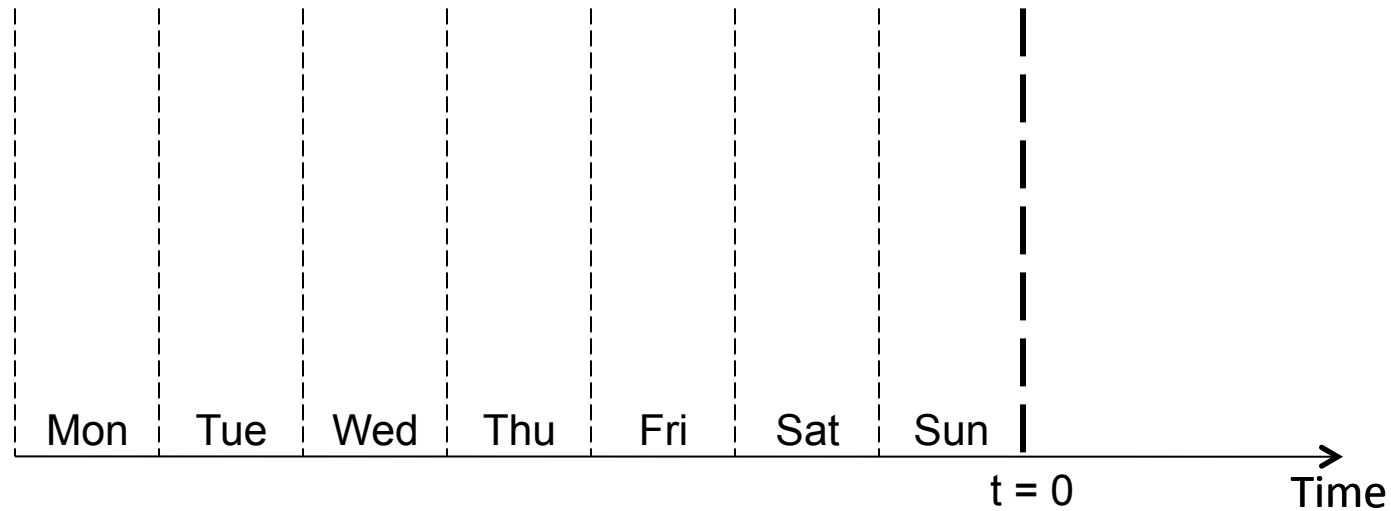
The single deterministic forecast f_0 fails to predict the **TRUE**

The initial probability density function **PDF(0)** represents the initial uncertainties

An ensemble of perturbed forecasts f_i , starting from perturbed initial conditions designed to sample the initial uncertainties can be used to estimate the probability of future states **PDF(t)**

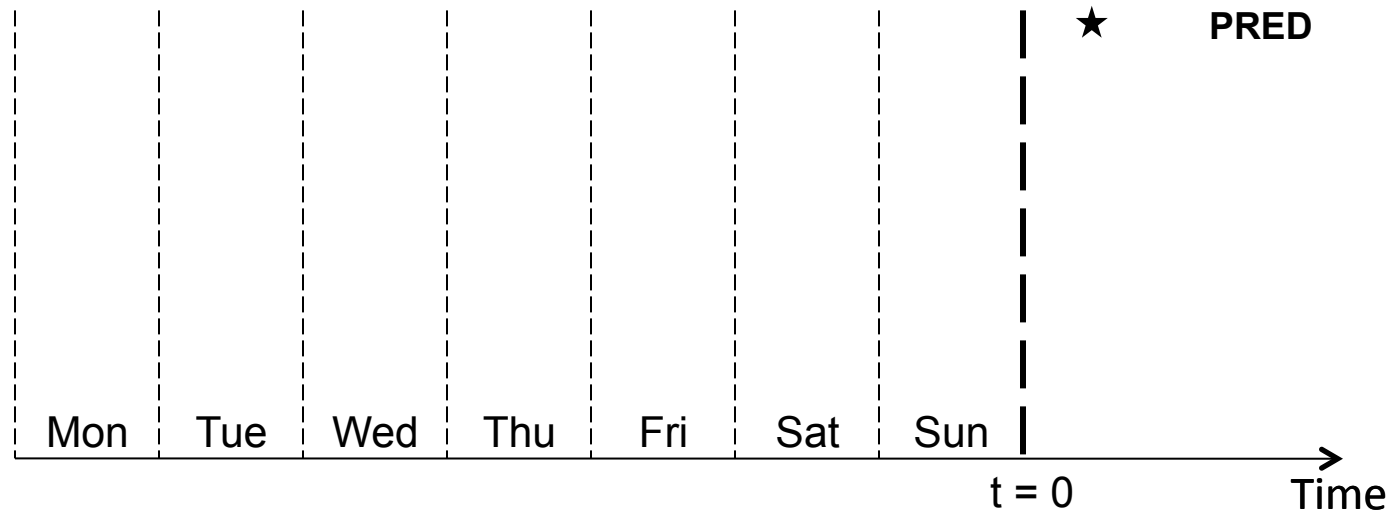


Analog Ensemble (AnEn)



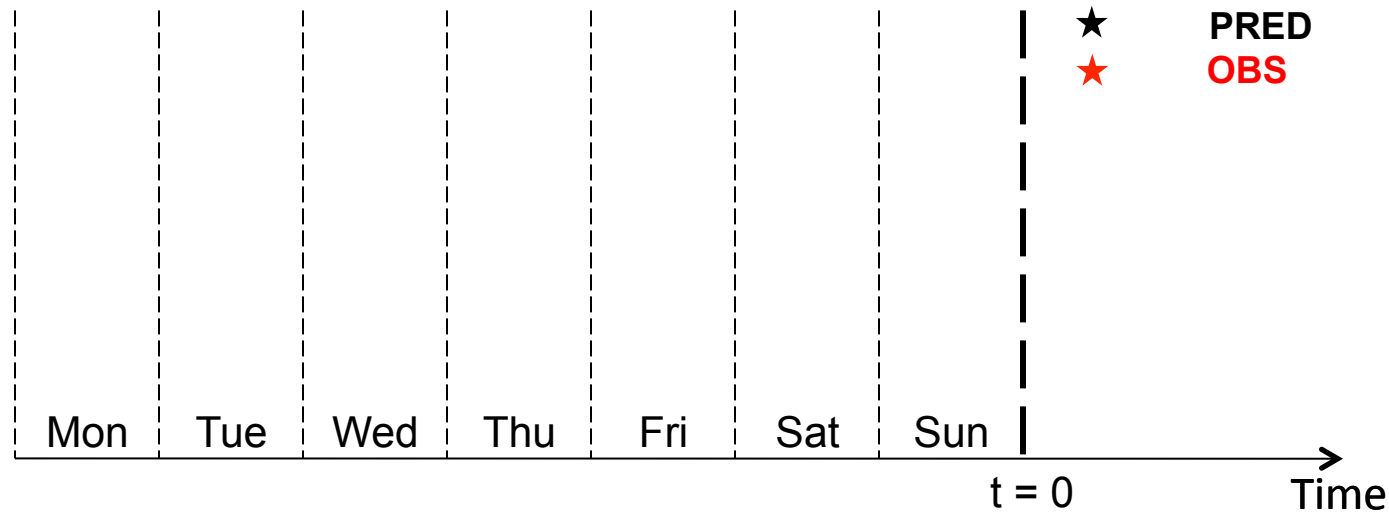
Analog search as in Delle Monache et al. (MWR 2011)

Analog Ensemble (AnEn)



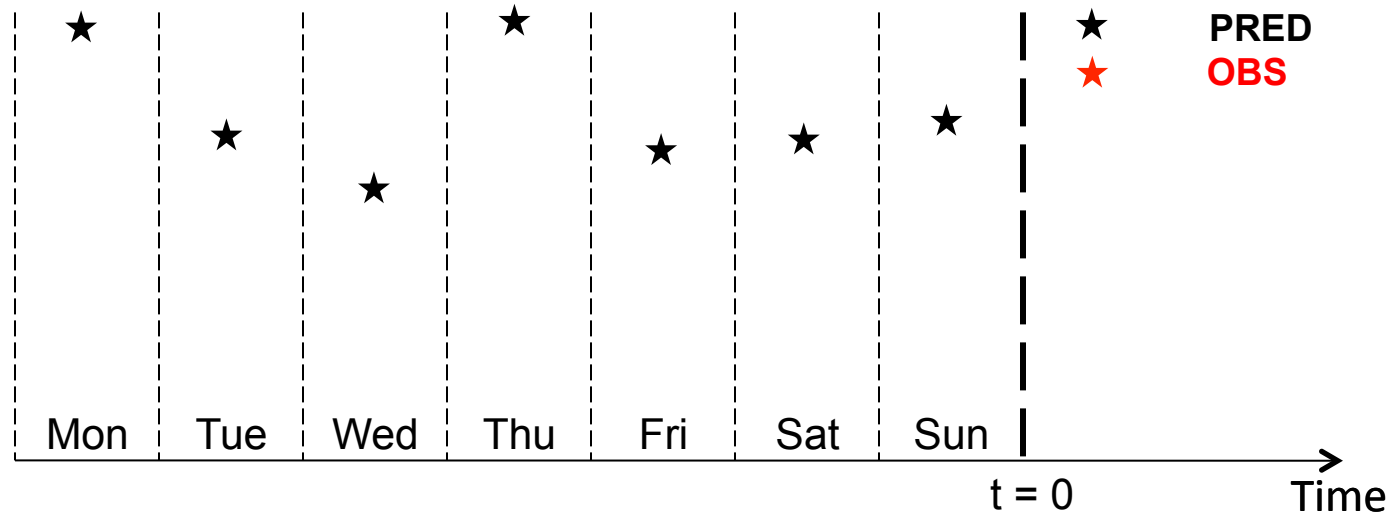
Analog search as in Delle Monache et al. (MWR 2011)

Analog Ensemble (AnEn)



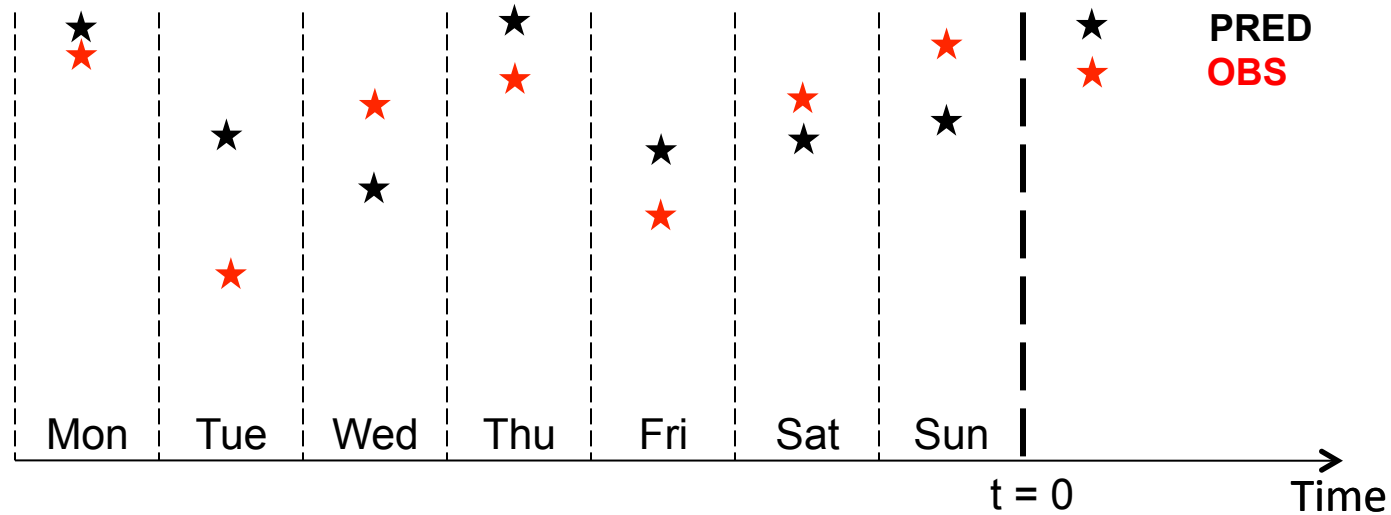
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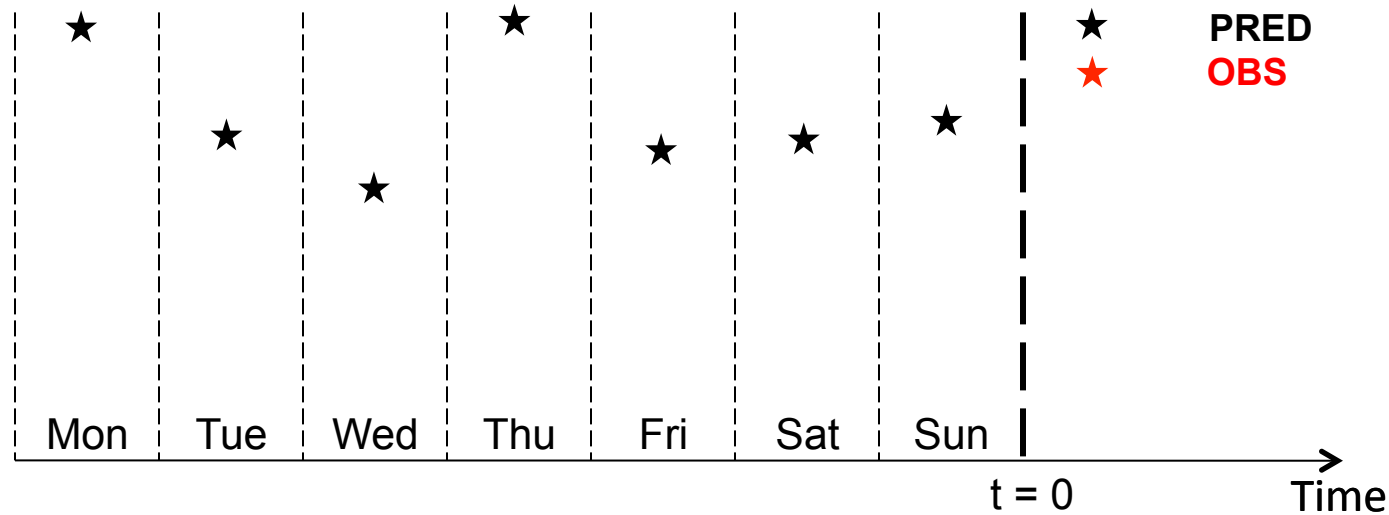
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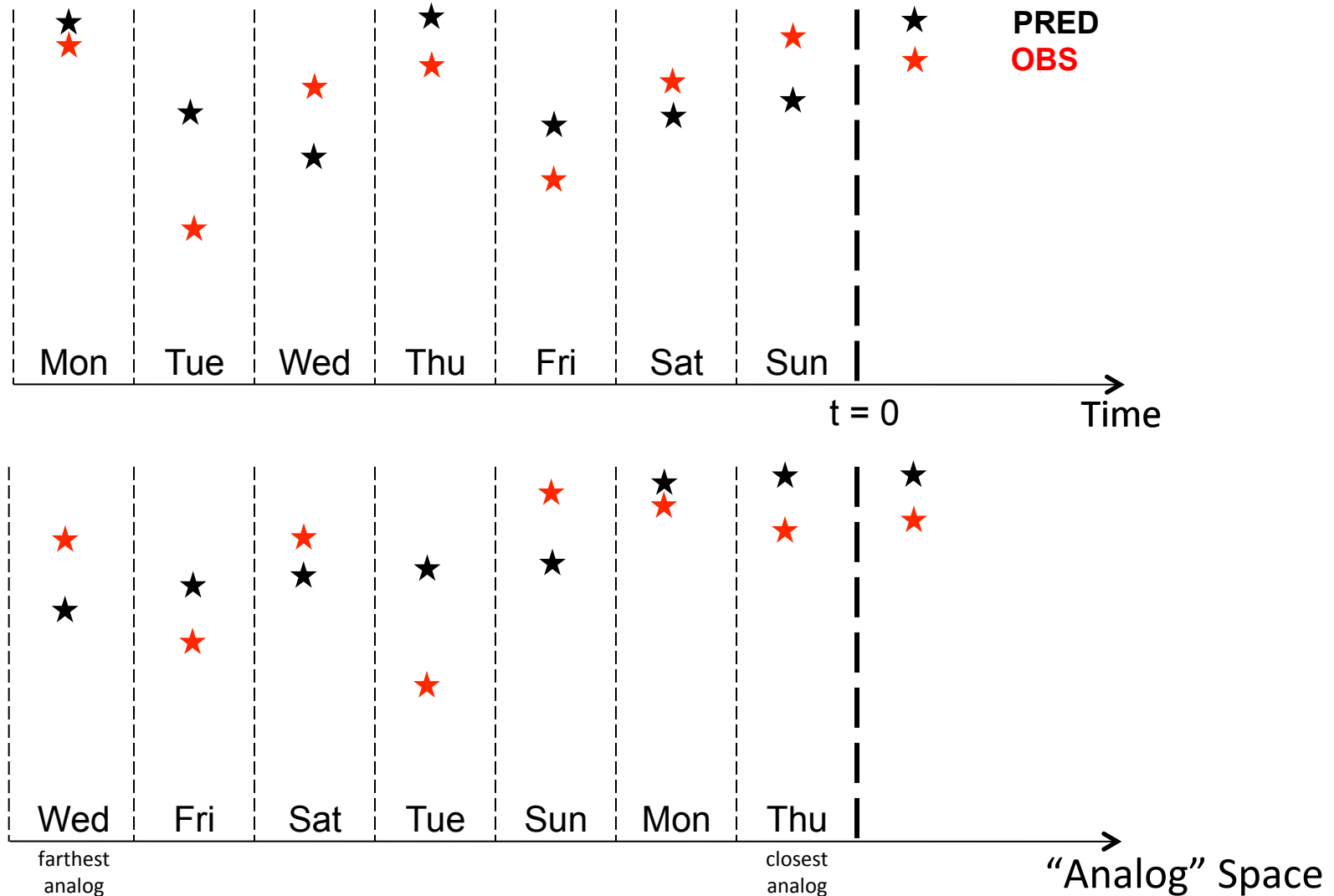
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Analog Ensemble (AnEn)



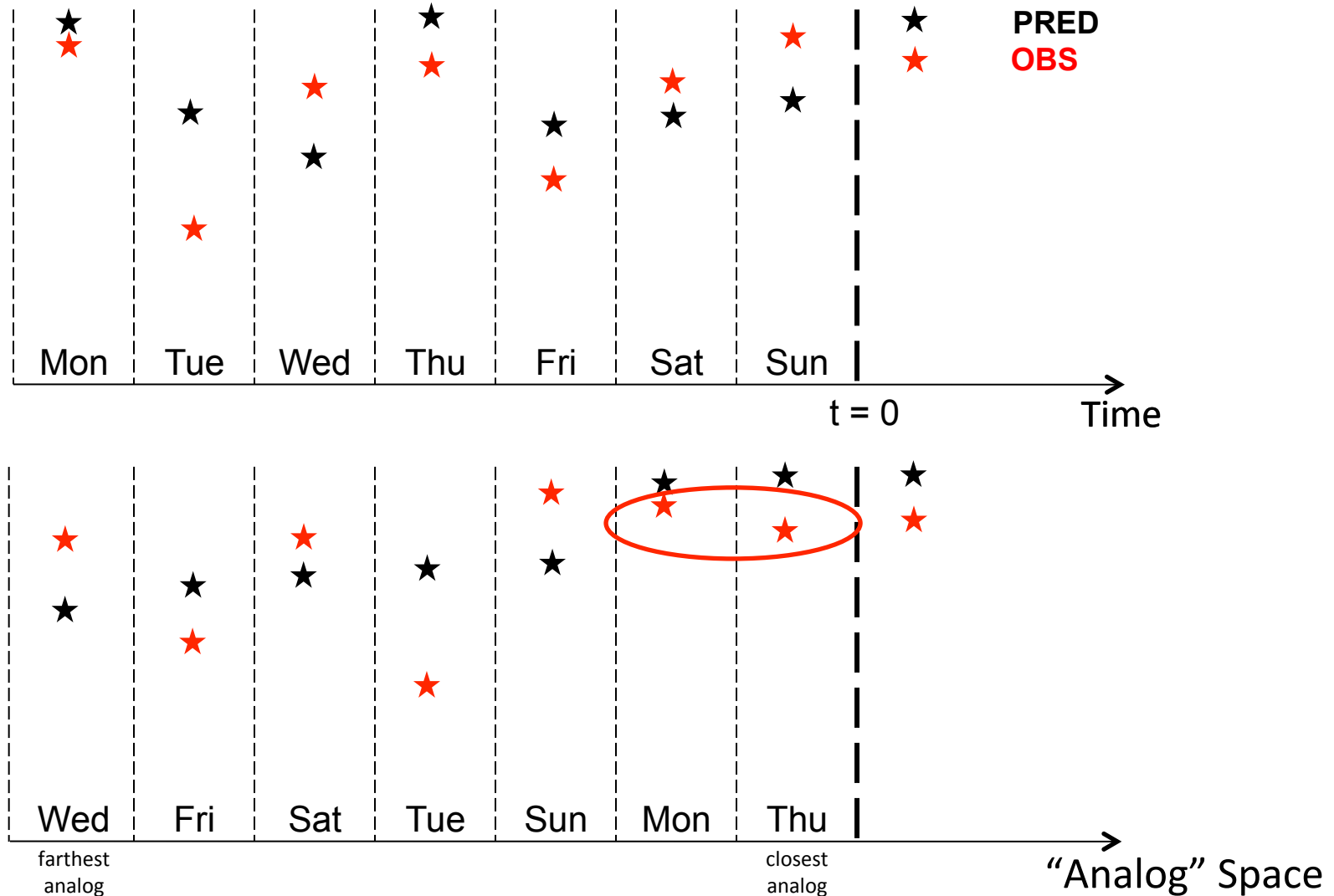
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Analog Ensemble (AnEn)



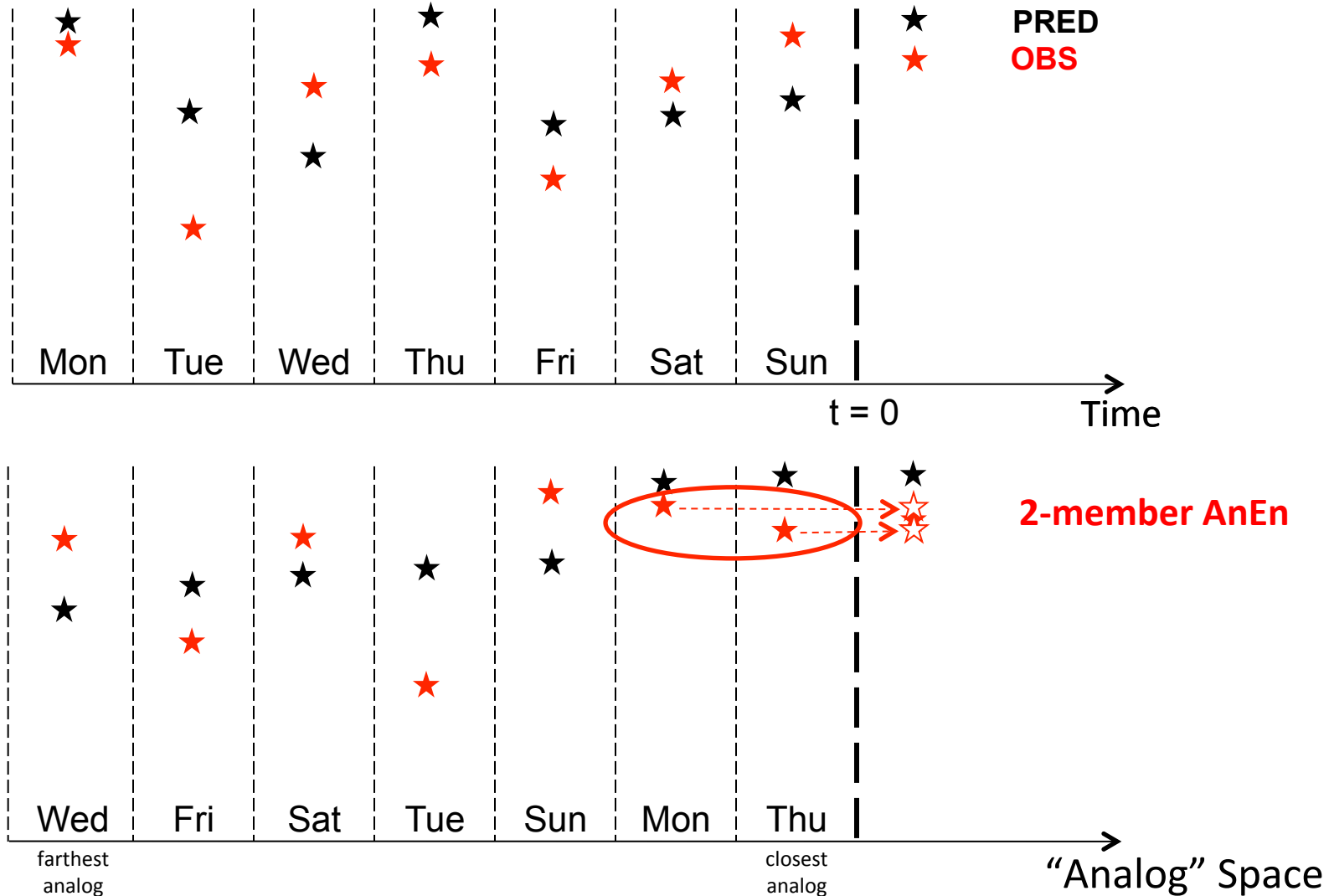
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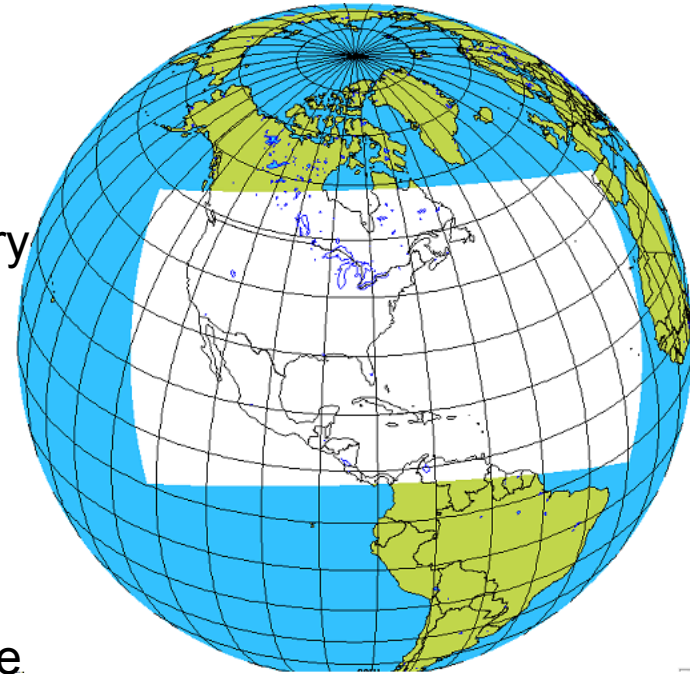
Analog search as in Delle Monache et al. (MWR 2011)

How skillful is AnEn?

- AnEn generated with Environment Canada GEM (15 km), 0-48 hours
- Comparison with:
 - Environment Canada Regional Ensemble Prediction System (REPS, next slide)
 - Logistic Regression (LR) out of 15-km GEM
 - LR out of REPS, i.e., Ensemble Model Output Statistics (EMOS)
- Period of 15 months (verification over the last 3 months)
- 10-m wind speed
- 550 surface stations over CONUS (in two slides)
- Probabilistic prediction attributes: statistical consistency, reliability, sharpness, resolution, spread-error consistency

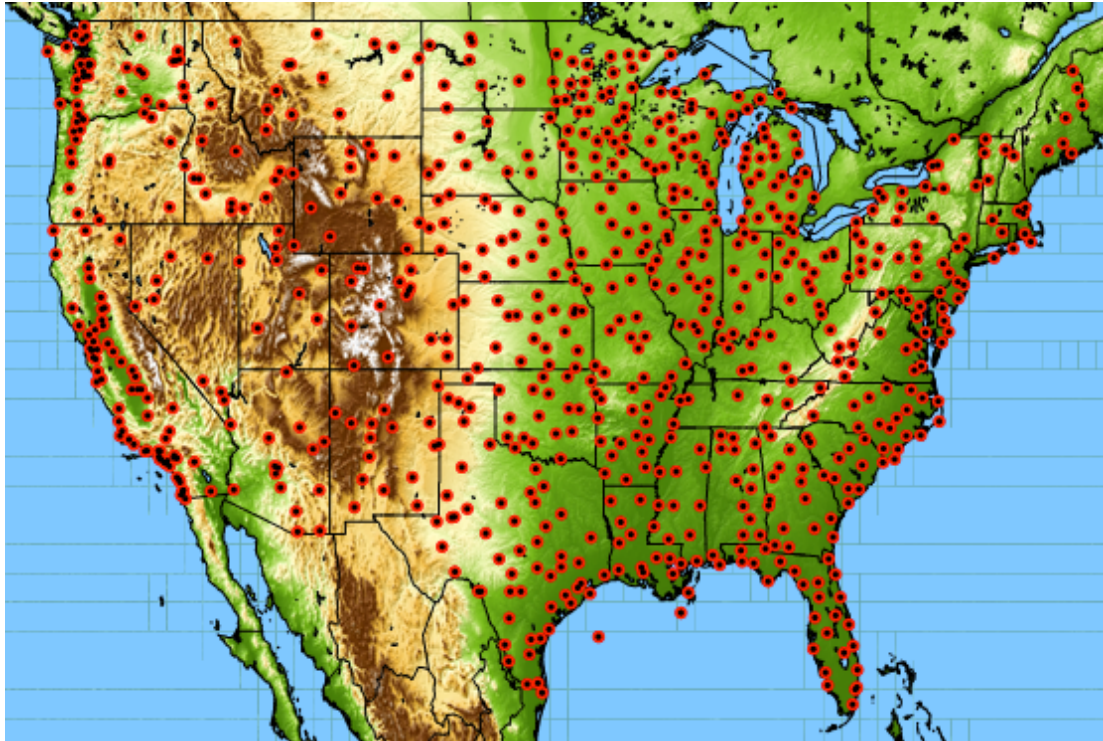
Regional Ensemble Prediction System (REPS)

- Model: GEM 4.2.0 (vertical staggering)
- 20 members + 1 control run
- 72 hours forecast lead time
- Resolution: ~33 km with 28 levels
- Initial conditions (i.e., cold start) and 3-hourly boundary condition updates from GEPS (EnKF + multi-physics)
- Physics:
 - Kain et Fritsch (1993) for deep convection
 - Li et Barker (2005) for the radiation
 - ISBA scheme (Noilhan et Planton, 1989) for surface
- Stochastic Physics: Markov Chains on physical tendencies



Ground truth dataset

- 550 hourly METAR Surface Observations
- 1 May 2010 – 31 July 2011, for a total of 457 days
- 10-m wind speed



Probabilistic forecast attributes: Reliability

Example:

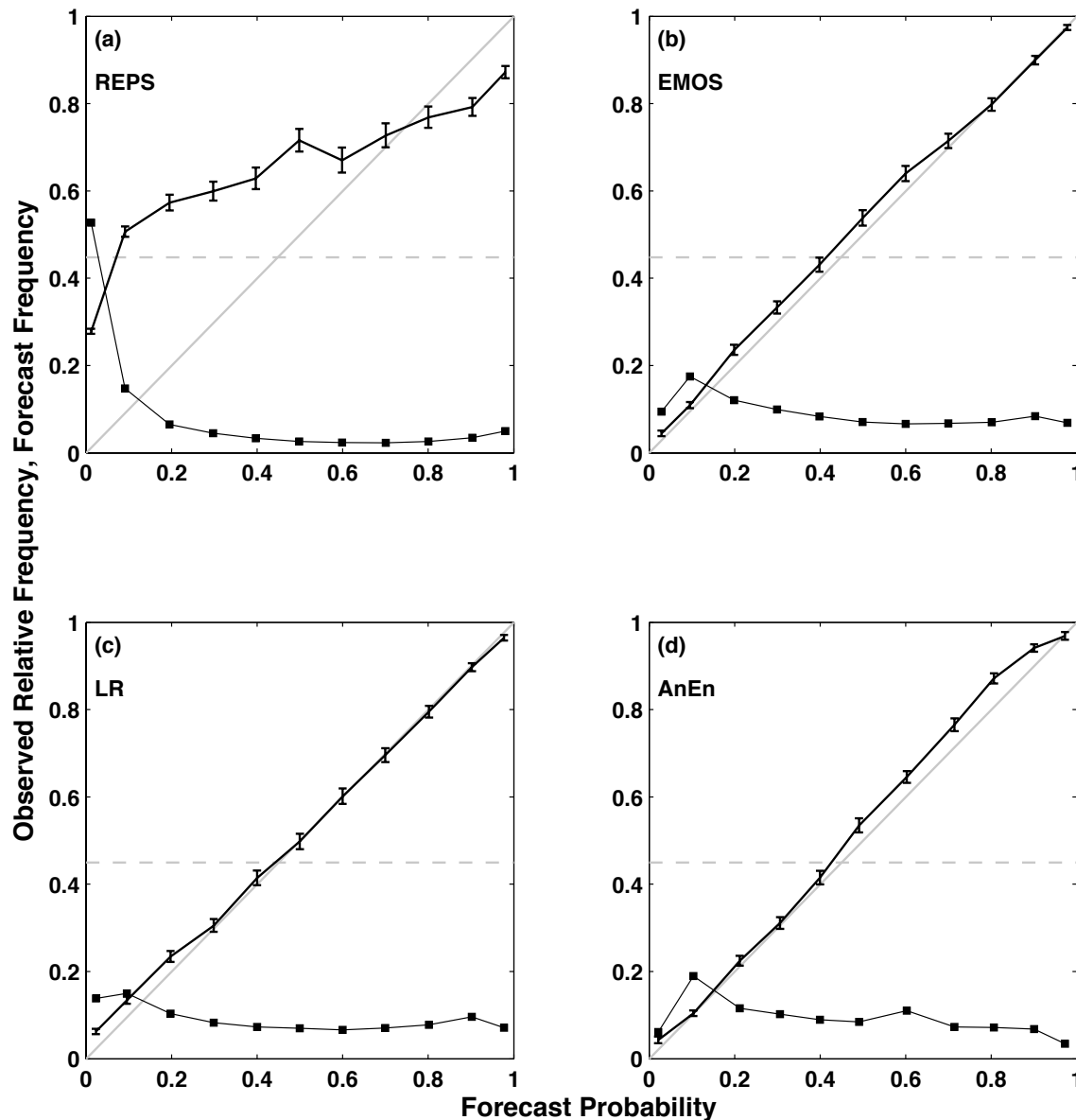
- ① An event (e.g., wind speed > 5 m/s) is predicted to happen with a 30% probability
- ② We collect the observations that verified every time we made the prediction in ①
- ③ If the frequency of the event in the observation collected is 30%, then the forecast is perfectly *RELIABLE*

Analysis of reliability & sharpness



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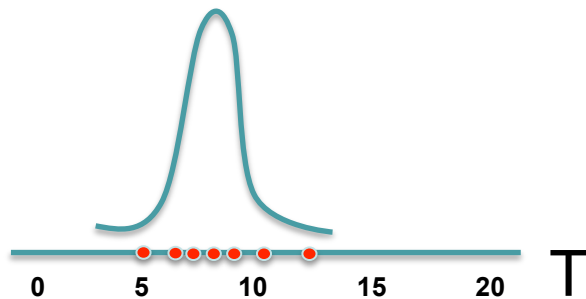
Reliability and sharpness diagram: 10-m wind speed > 5 m s⁻¹, 9-h fcst



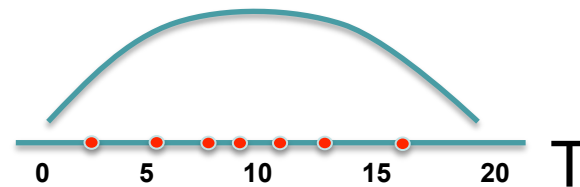
Probabilistic forecast attributes: Sharpness

Sharpness refers to the degree of concentration of a forecast PDF's probability density, and is a property of the forecasts only.

Ideally, we want the forecast system, while mainly reliable, with as many forecasts as possible close to 0% and 100%, corresponding to a perfect deterministic forecast system. However, an improvement in sharpness does not necessarily mean that the forecast system has improved.



Sharper Forecast



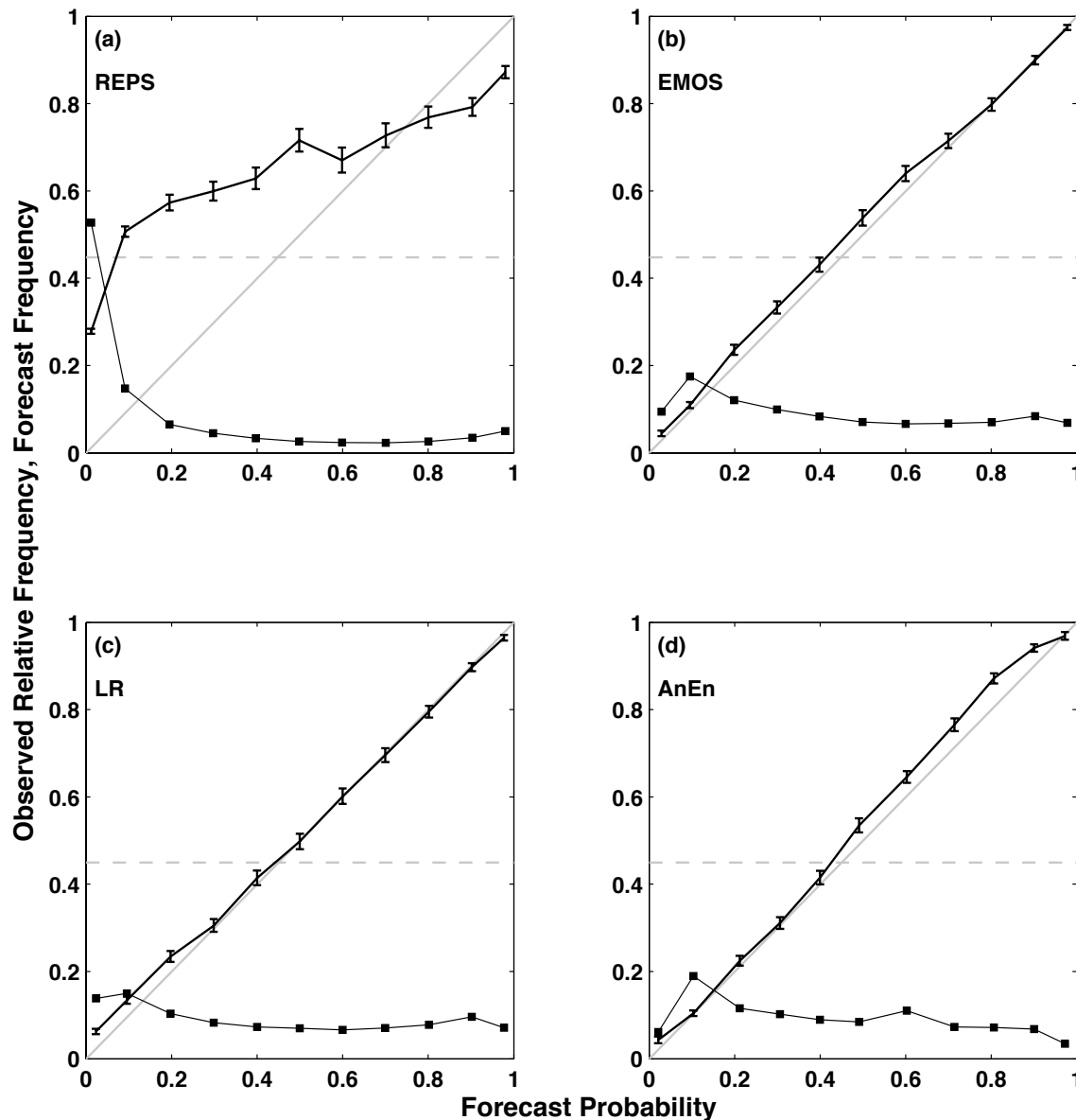
Less Sharp Forecast

Analysis of reliability & sharpness



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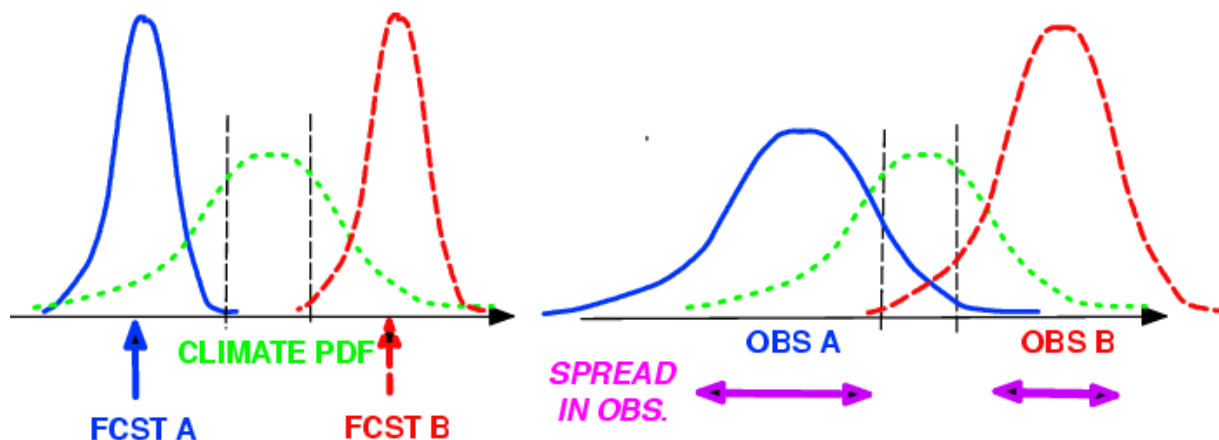
Reliability and sharpness diagram: 10-m wind speed > 5 m s⁻¹, 9-h fcst



Probabilistic forecast attributes: Resolution



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Consider different classes of forecast events.

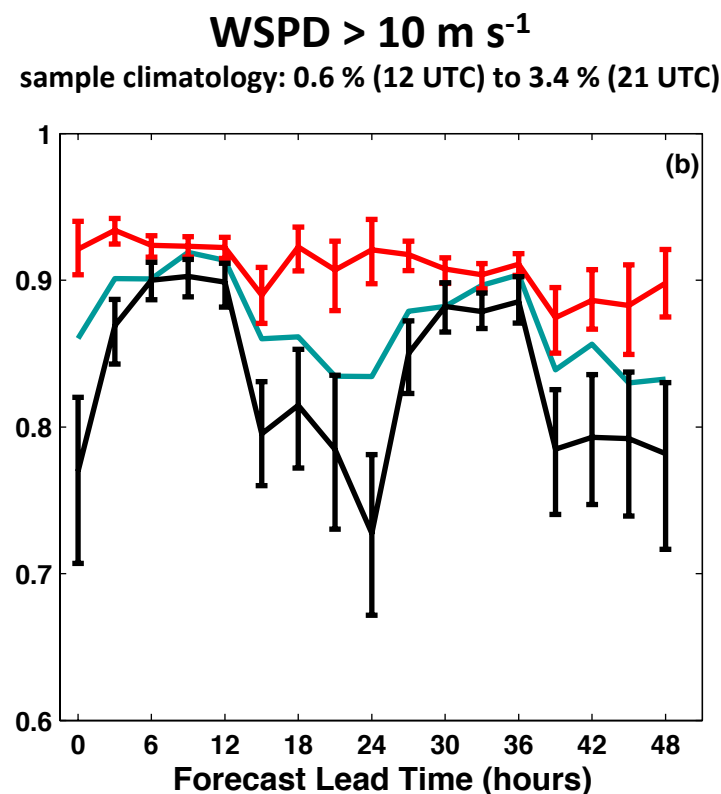
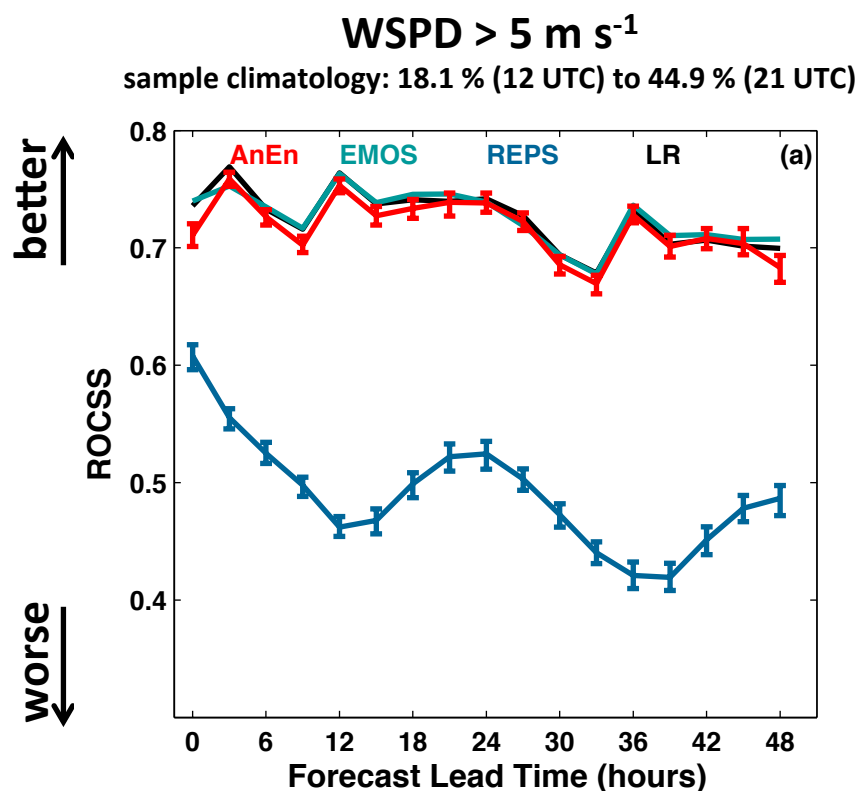
If all observed classes corresponds to different forecast classes,
then the probabilistic forecast has perfect *RESOLUTION*.

Analysis of Resolution (1)



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Relative Operating Characteristics skill score, 10-m wind speed ≥ 5 , 10 m s^{-1}



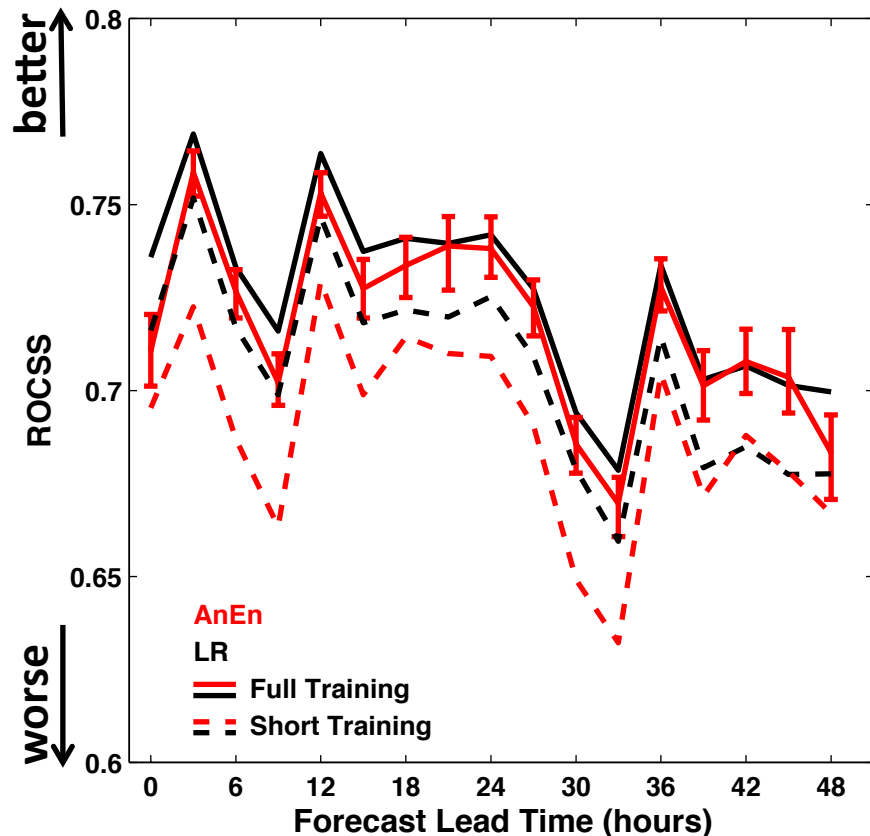
AnEn sensitivity



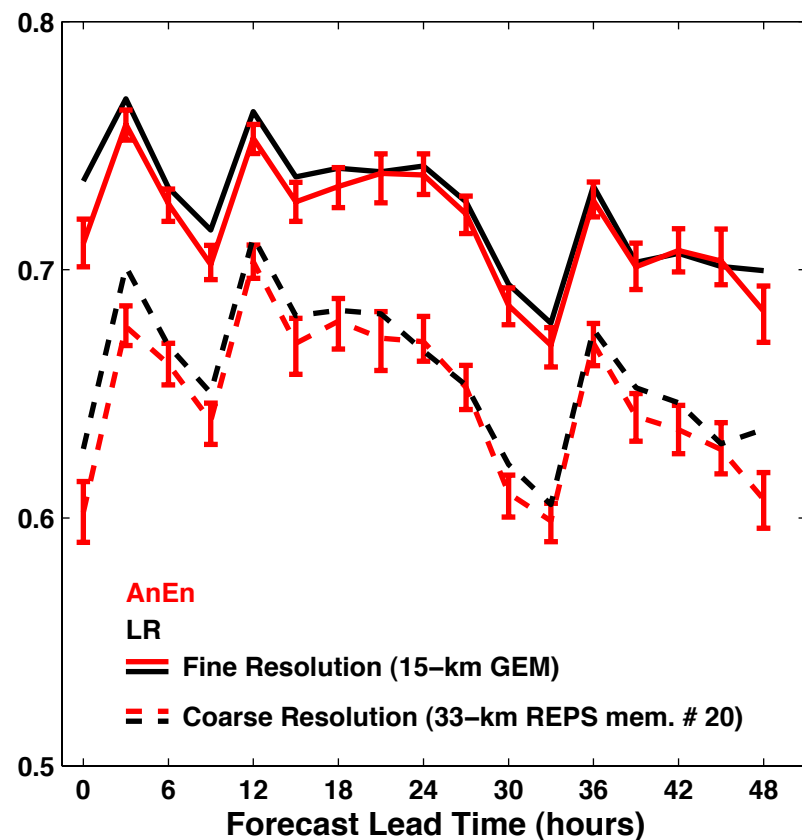
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Relative Operating Characteristics skill score, 10-m wind speed $\geq 5 \text{ m s}^{-1}$

AnEn with a shorter training data set (15 \rightarrow 9 months)



AnEn built with a coarser dynamical model (15 \rightarrow 33 km)



Probabilistic forecast attributes: Statistical and spread-error consistency

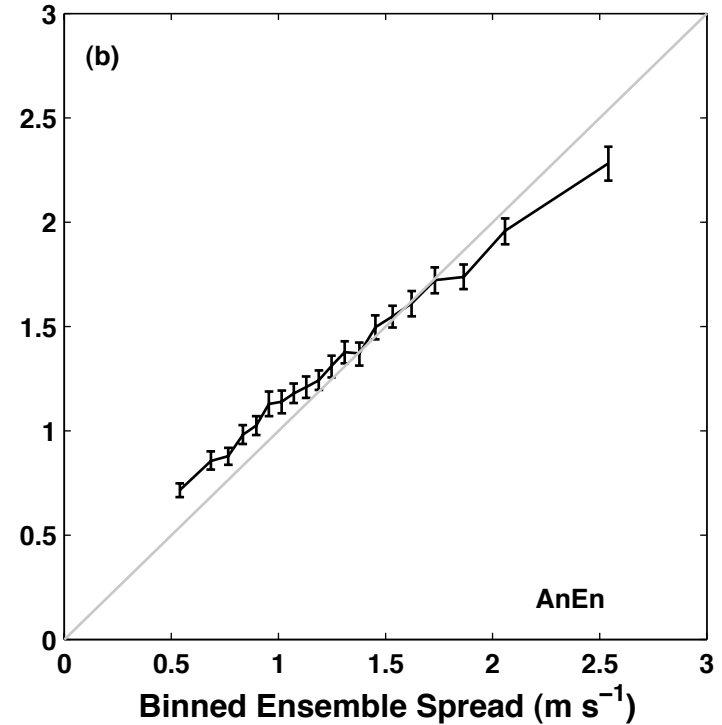
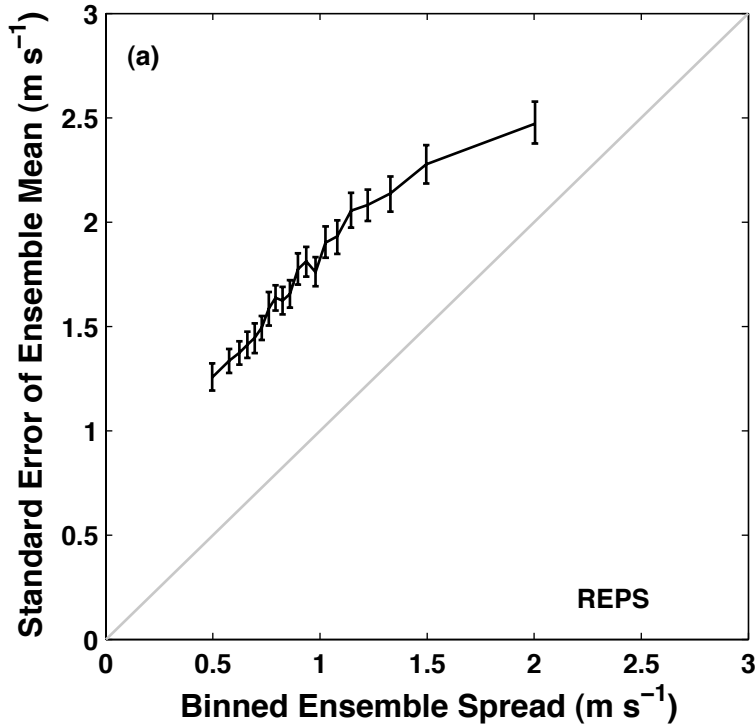
- ① The ensemble spread tell us how uncertain a forecast is. Ideally, large spread should be associate with larger uncertainties, low spread should indicate higher accuracy
- ② If an ensemble is perfect, than the observations are indistinguishable from the ensemble members

Analysis of spread-error consistency (2)

Binned spread-skill diagram, 10-m wind speed, 42-h fcst



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Probabilistic power prediction with an analog ensemble

Goal:

Accurate power forecasts and reliable quantification of forecast uncertainty

Motivation:

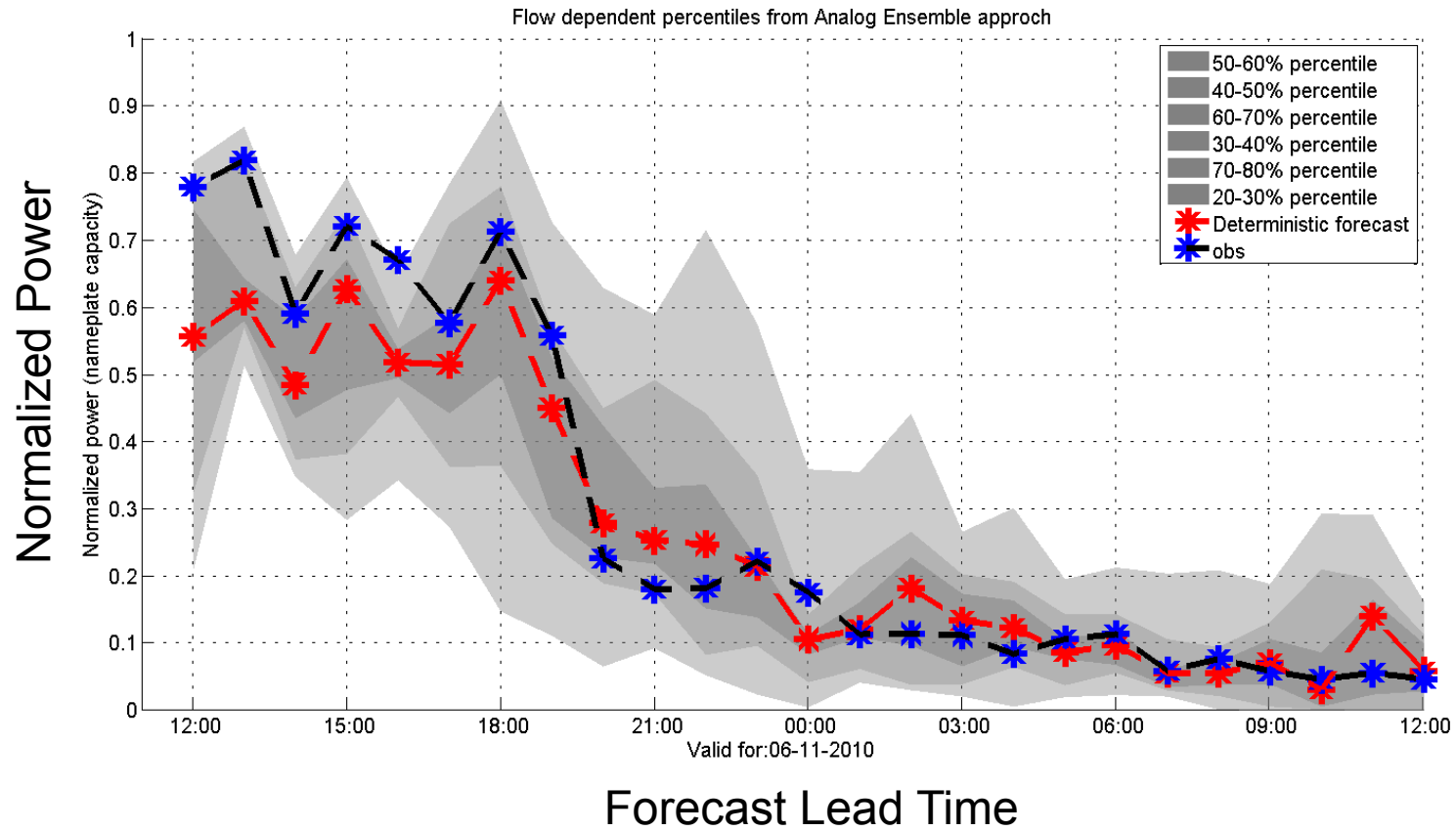
- Increase wind energy penetration in the energy market
 - Optimized Servicing
 - Less spinning reserves needed and optimized servicing of wind individual turbines

Power predictions: Experiment design

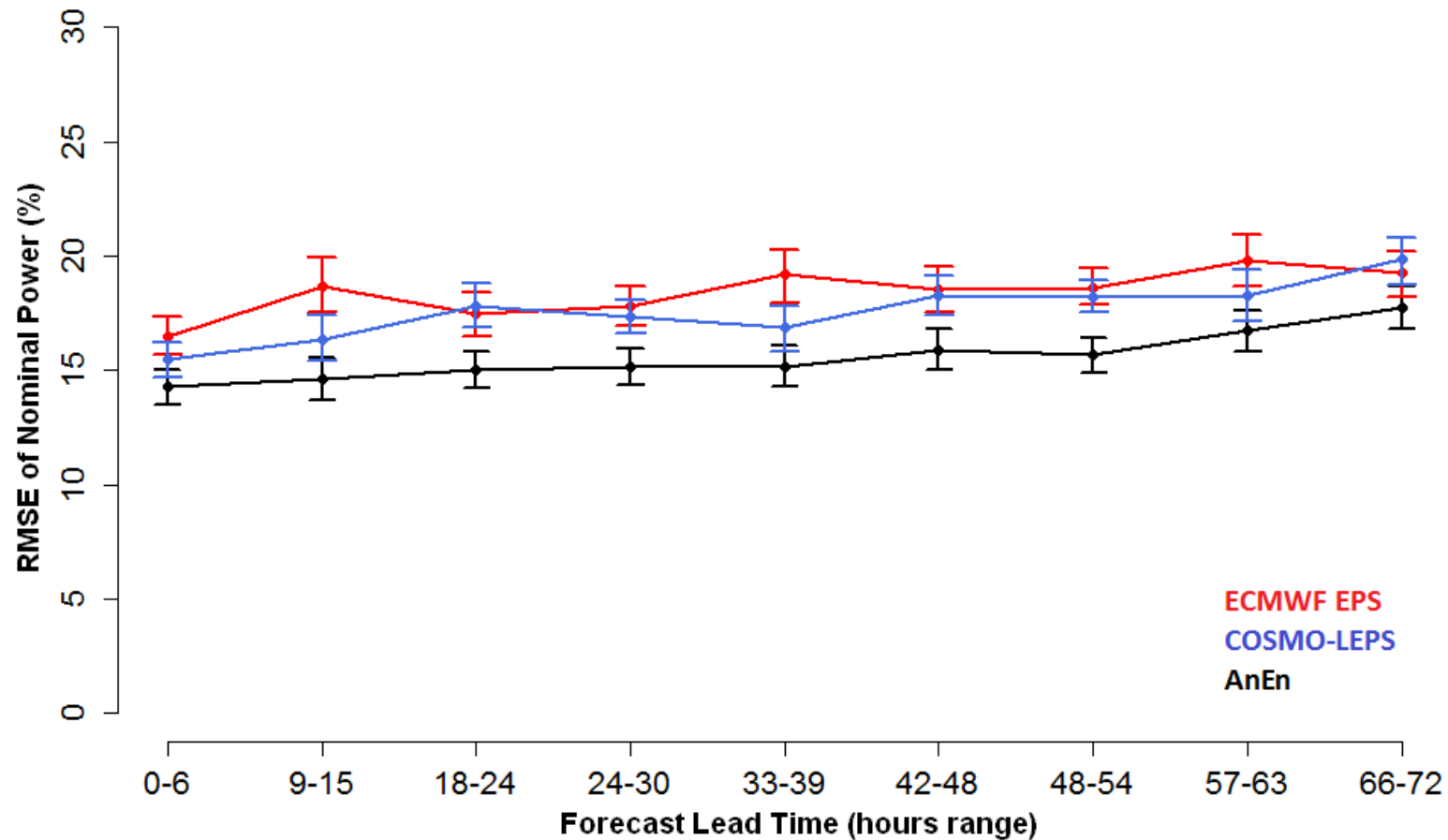


- Test site: Wind farm in northern Sicily – 9 turbines, 850 kW Nominal Power (NP)
- Training period: November 2010 - October 2012
- Verification period: November 2011 – October 2012
- Probabilistic prediction systems: ECMWF EPS, COSMO LEPS, AnEn

Power predictions



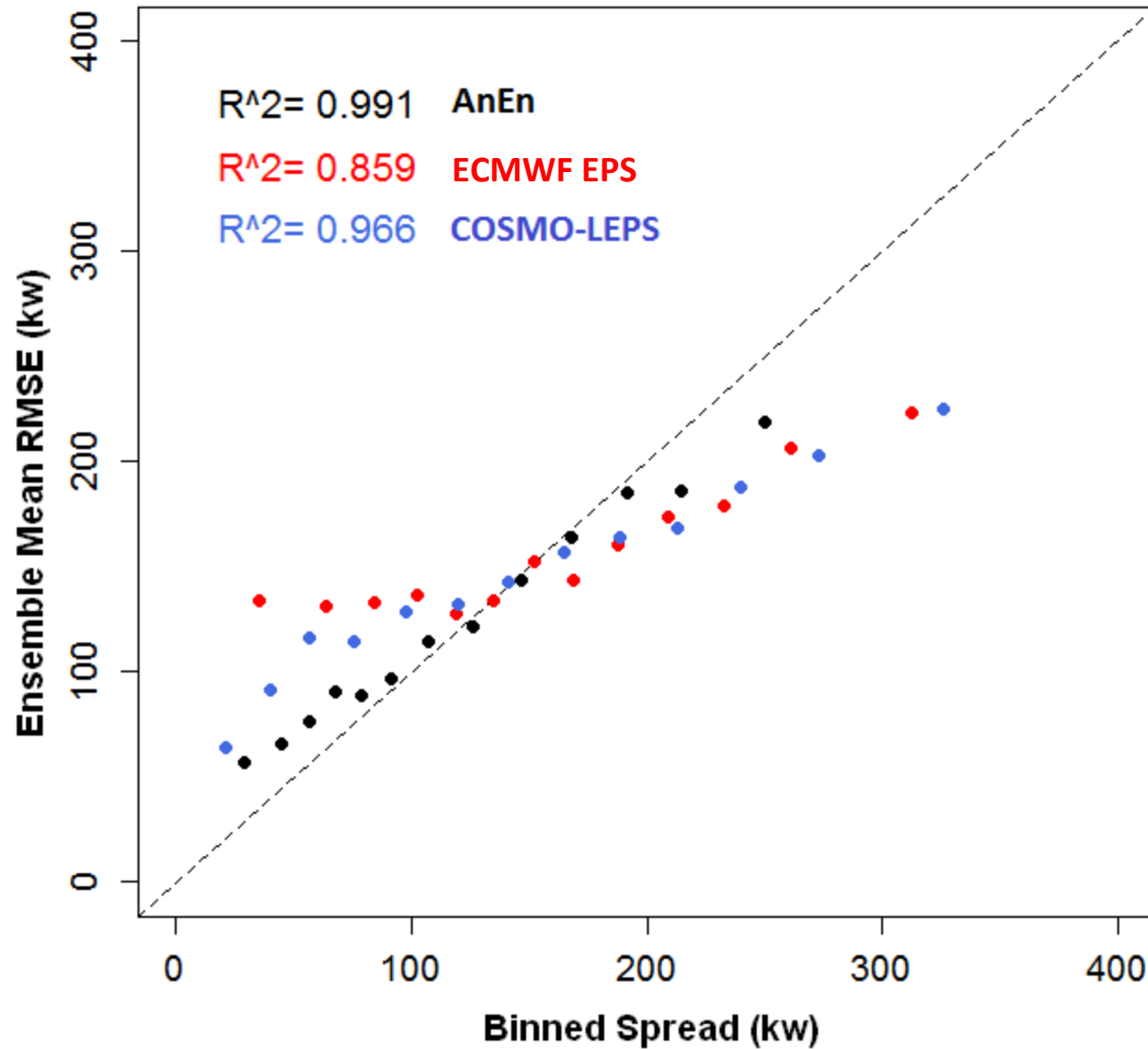
RMSE of ensemble means



Spread-skill relationship



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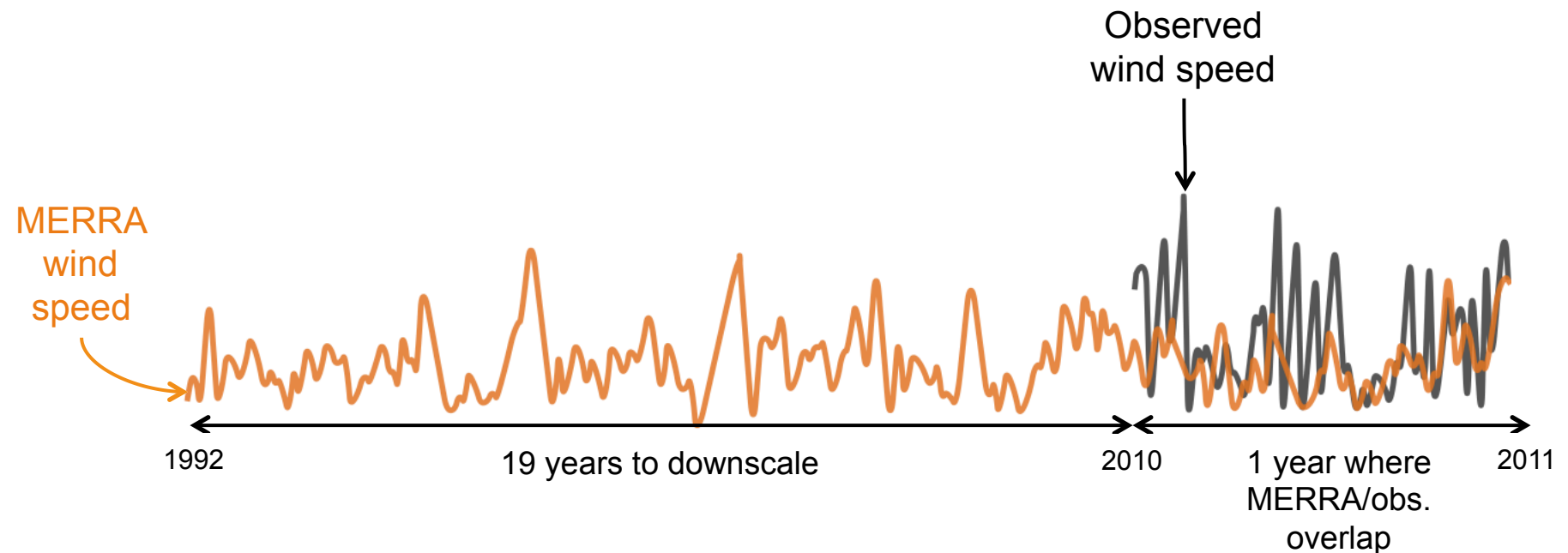
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AnEn for wind resource assessment

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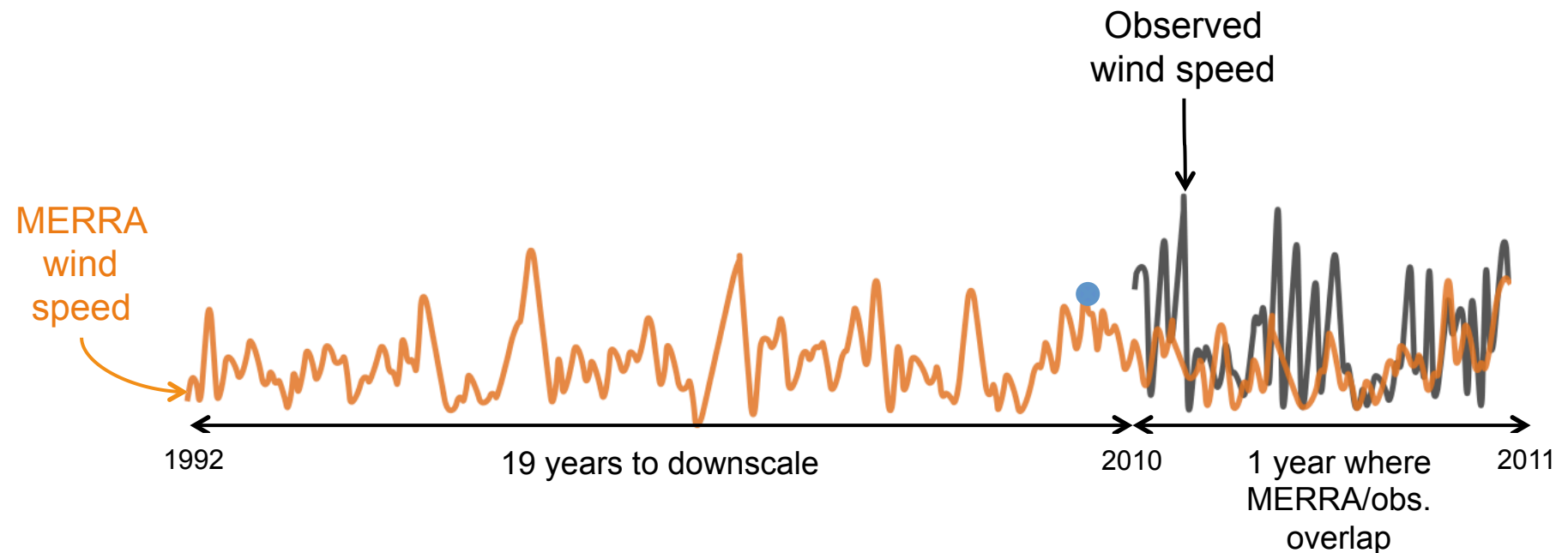
- Recreate a long-term observation-based wind climatology at site
- Downscale a long-term NASA Modern-Era Retrospective Analysis for Research and Applications (MERRA) time series using a short-term record of observations



AnEn for wind resource assessment

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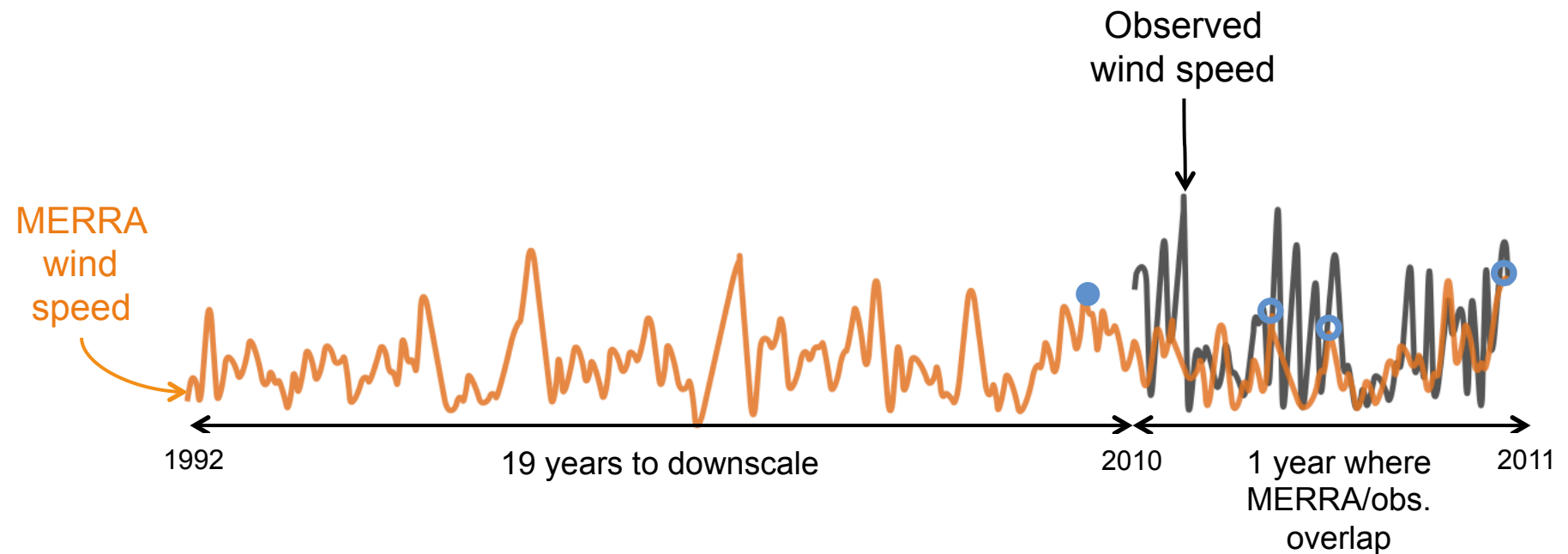
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AnEn for wind resource assessment

NCAR

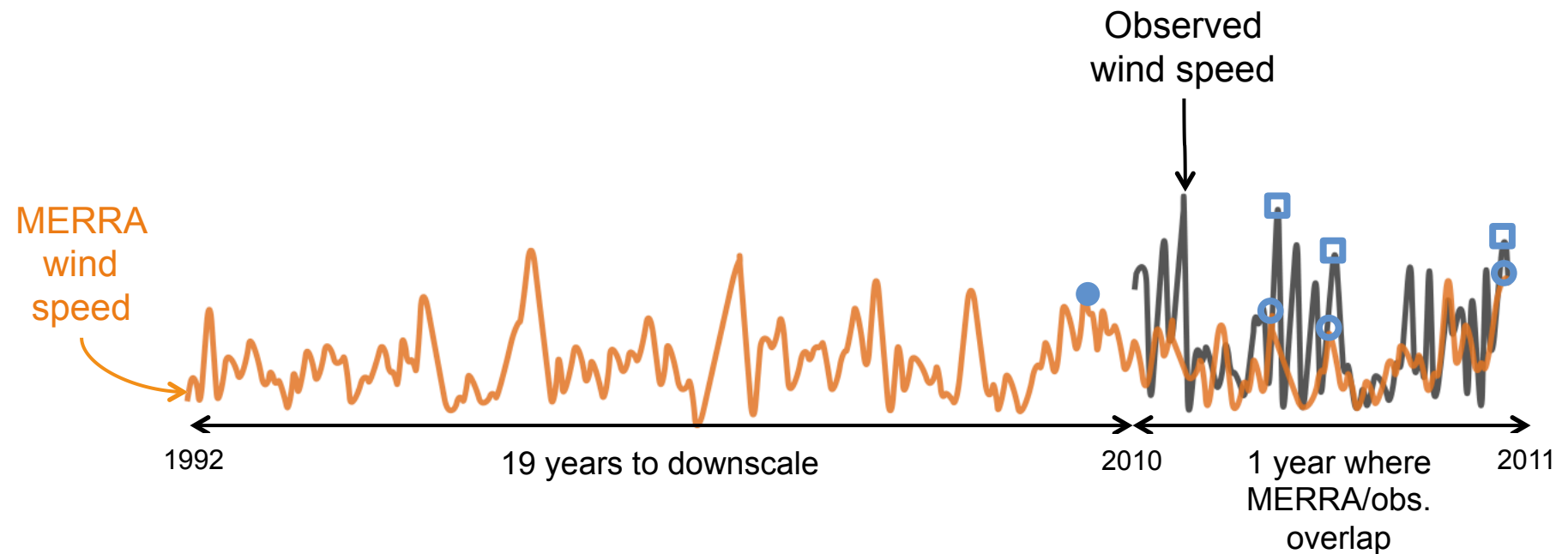
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AnEn for wind resource assessment

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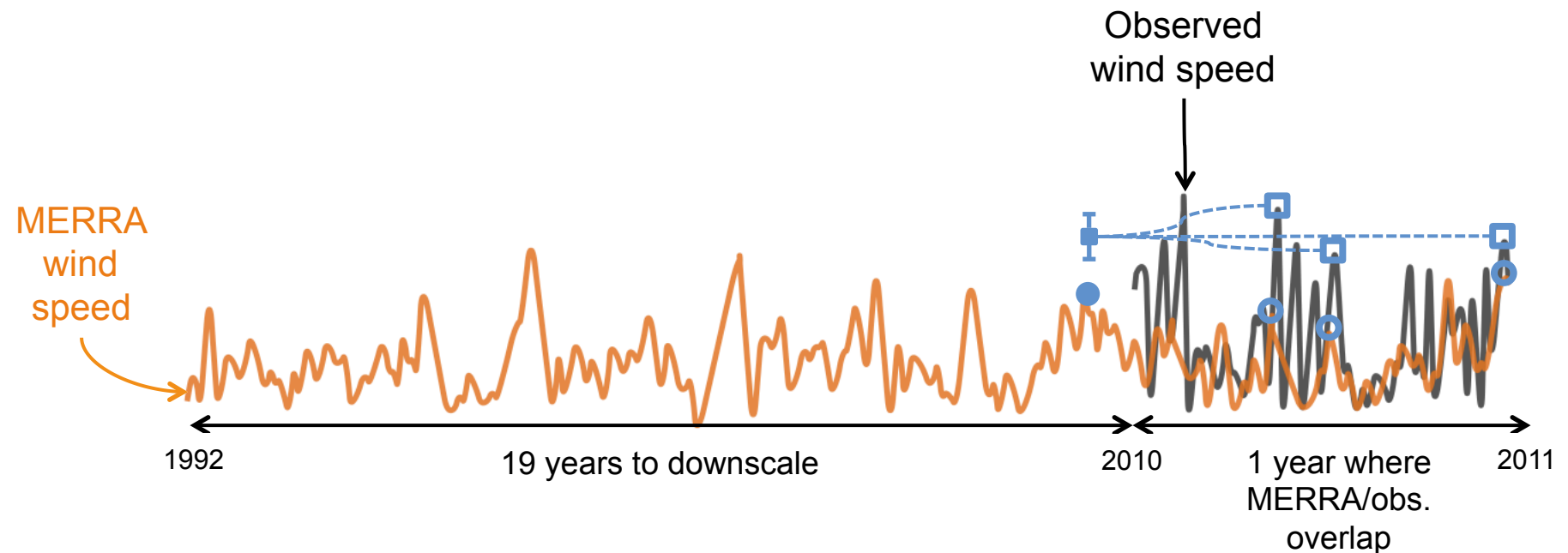
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AnEn for wind resource assessment

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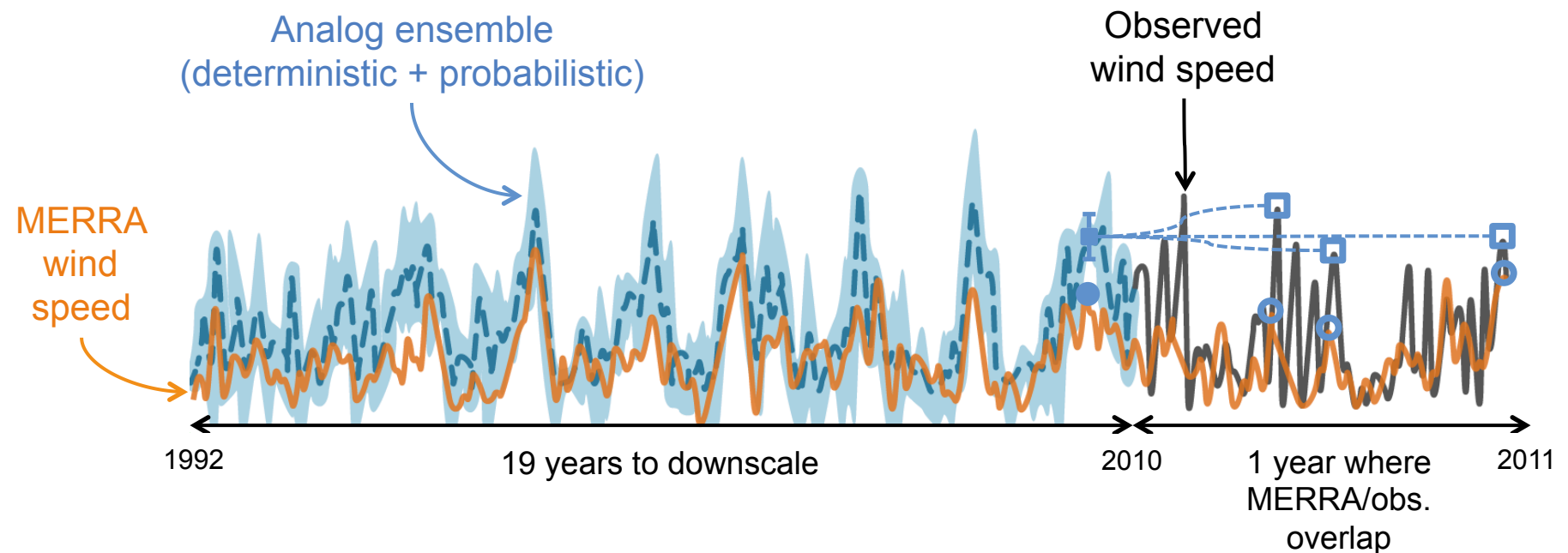
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AnEn for wind resource assessment

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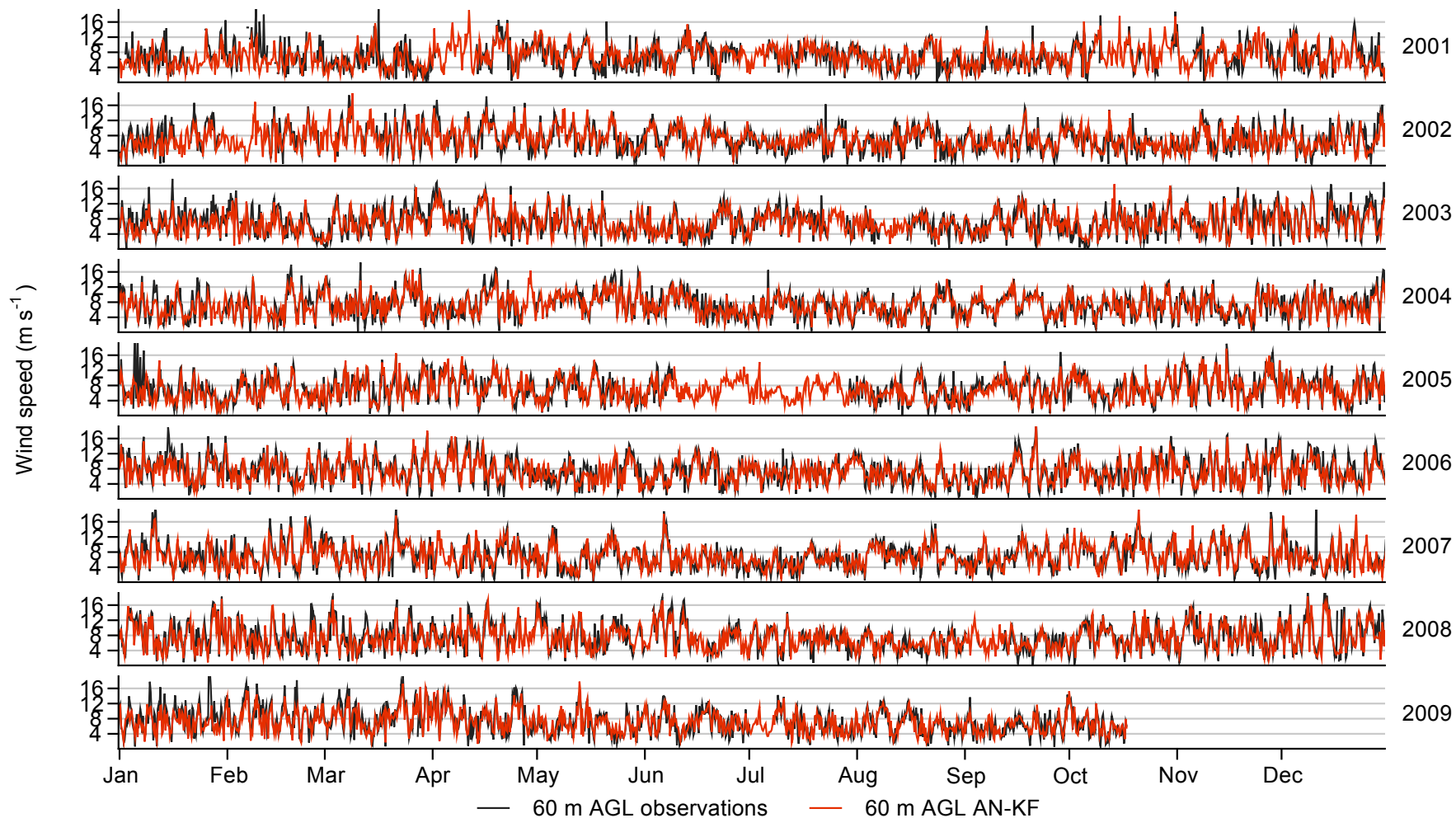


Results: example of time series (Lamont, OK)



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Lamont, OK: simple topography

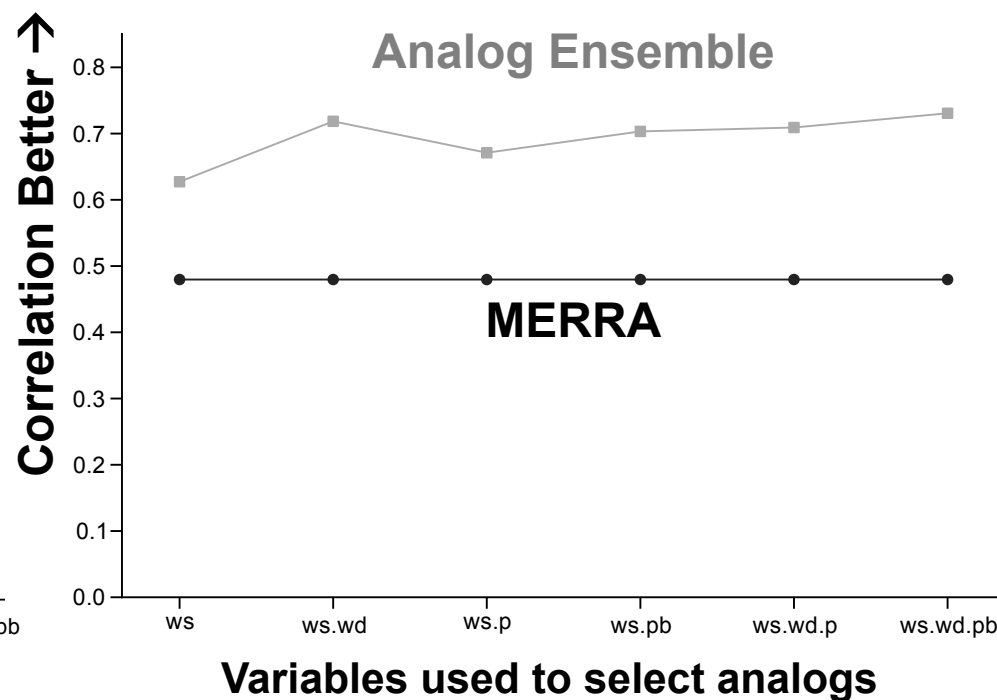
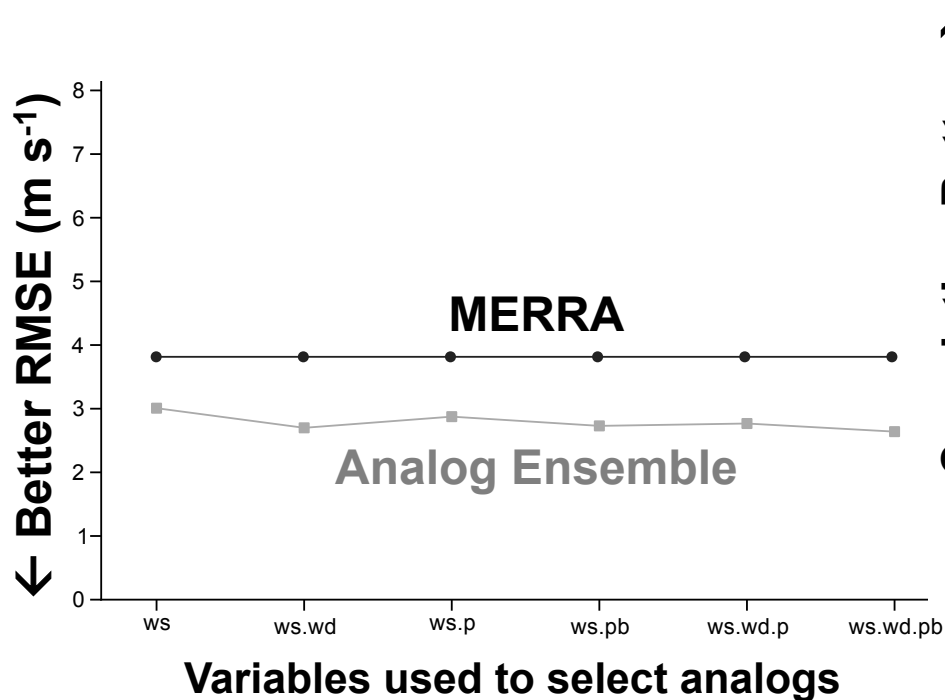


Training period: 2009-10-18 to 2010-10-17, downscale period: 2001-01-01 to 2009-10-17

Pearson $r^2 = 0.80$, Spearman $r = 0.89$ (across period shown; daily)

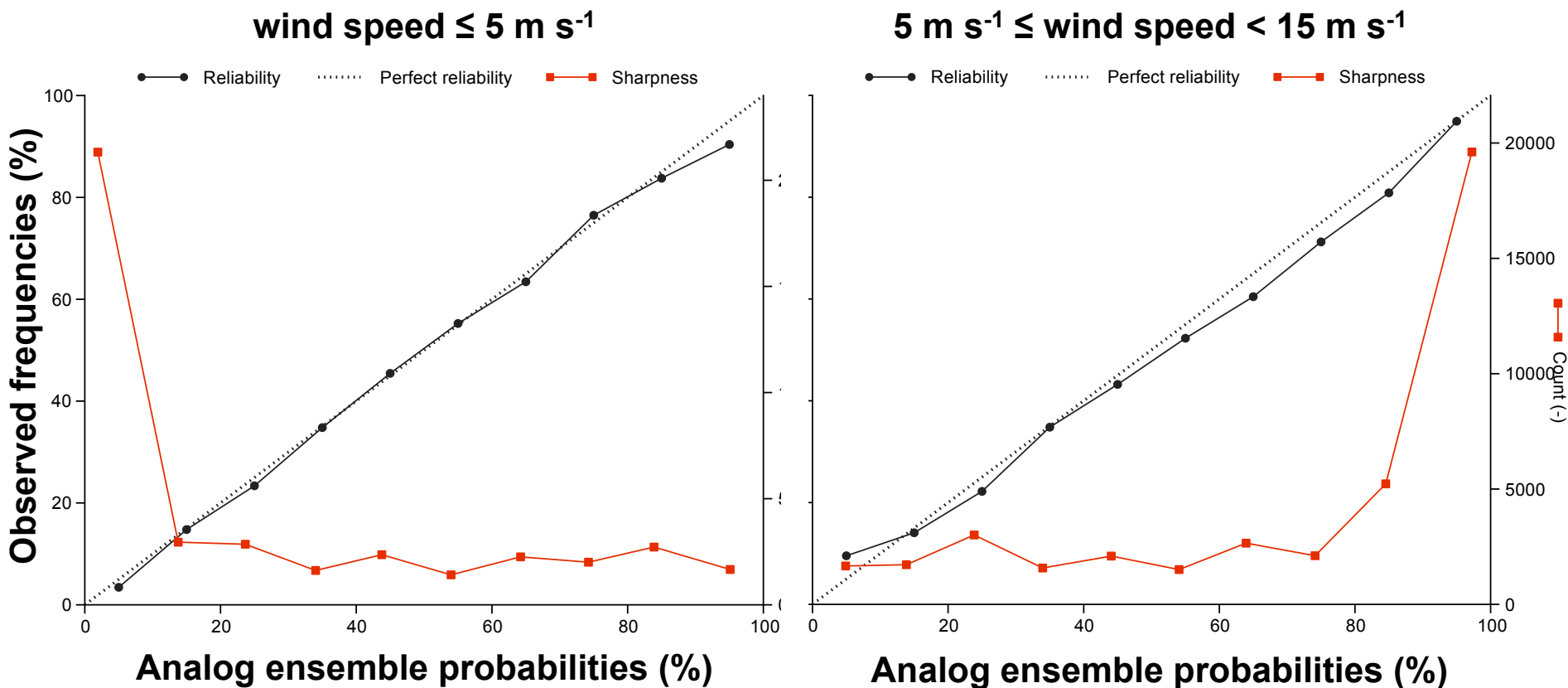
Deterministic results (Lamont, OK)

- Analog ensemble better than MERRA



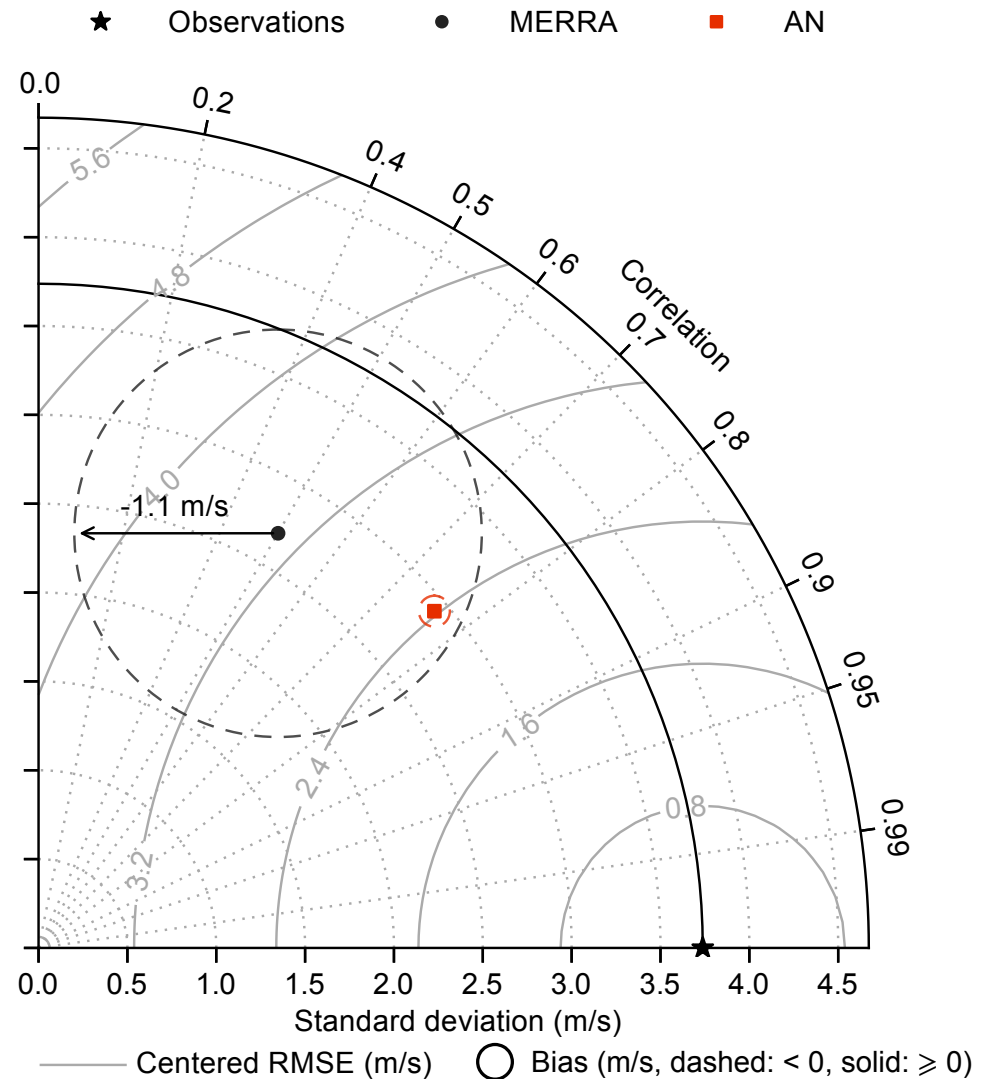
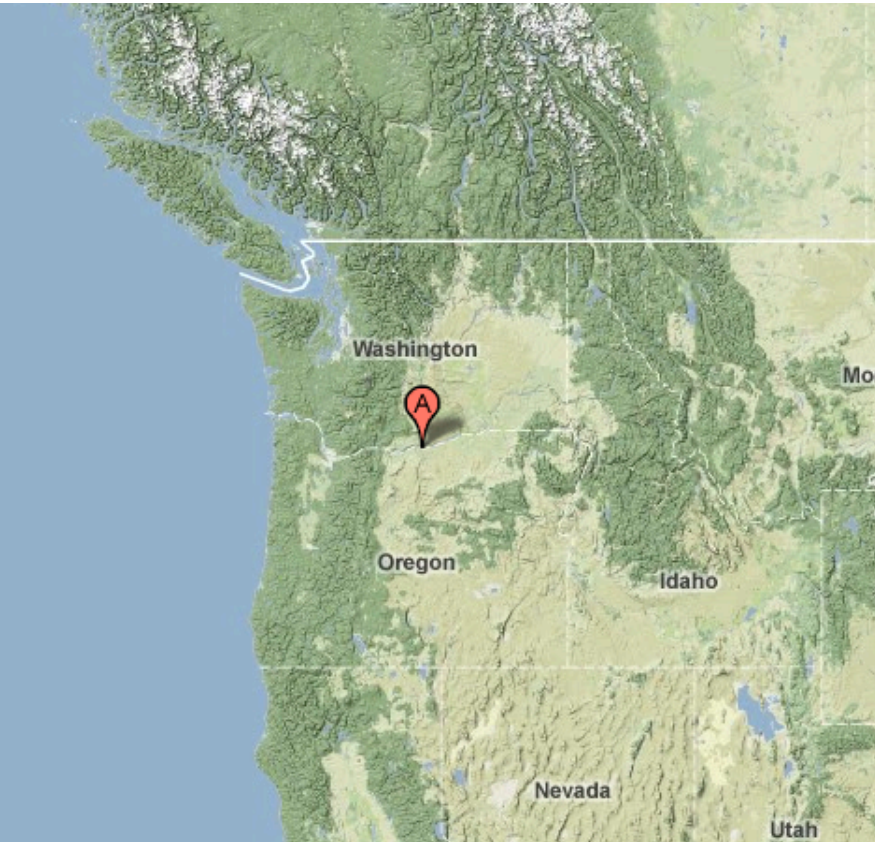
Probabilistic results (Lamont, OK)

- Analog ensemble provides reliable uncertainty estimates



Deterministic results (Goodnoe Hill, WA)

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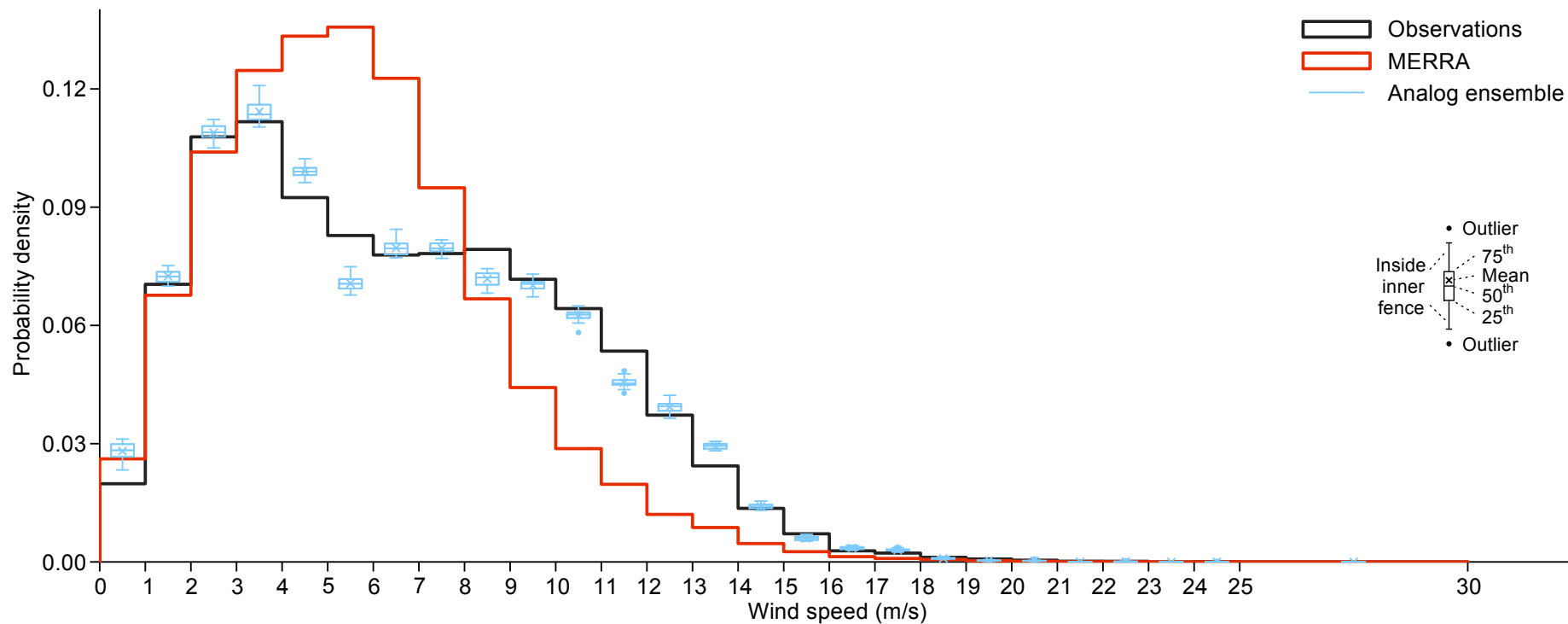


Training period: last 365 days, period downscaled: last 5 entire years, analogs: 25

PDFs comparison (Goodnoe Hill, WA)

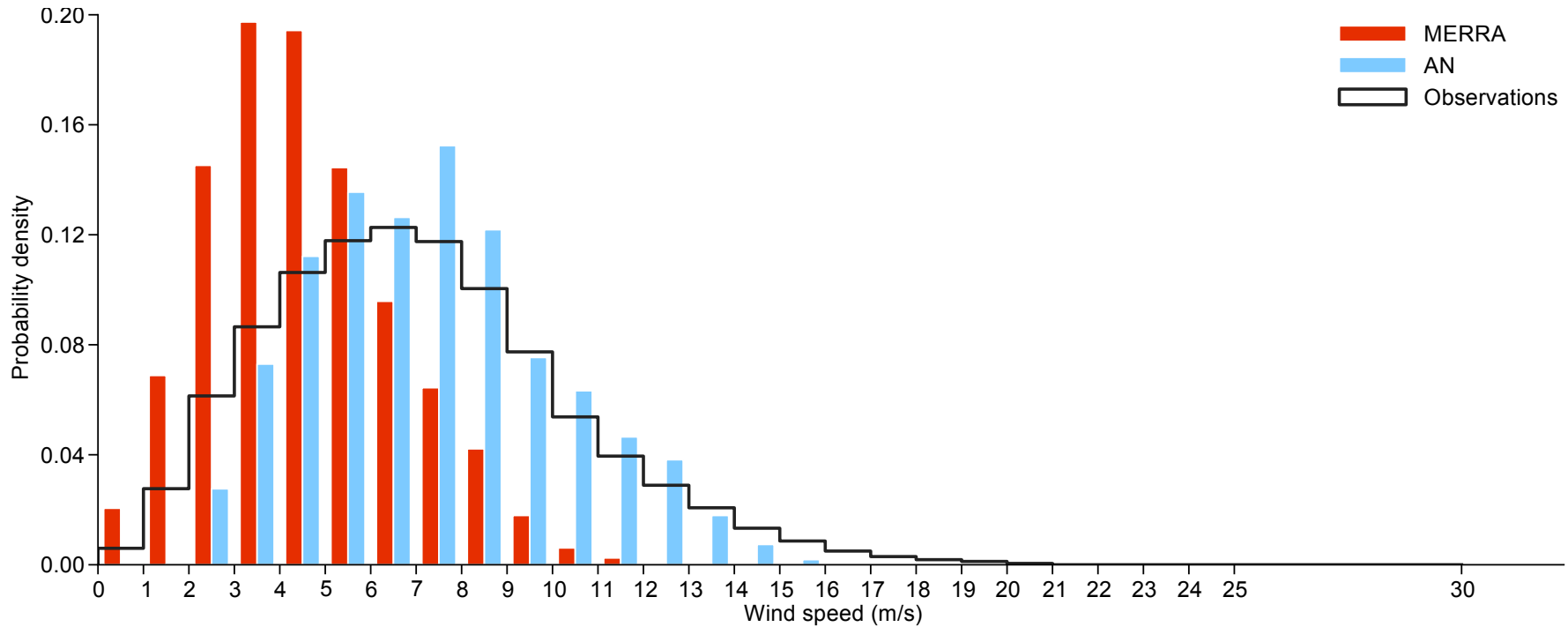


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Training period: last 365 days, period downscaled: last 5 entire years, analogs: 25

PDFs comparison (“Site 216”)



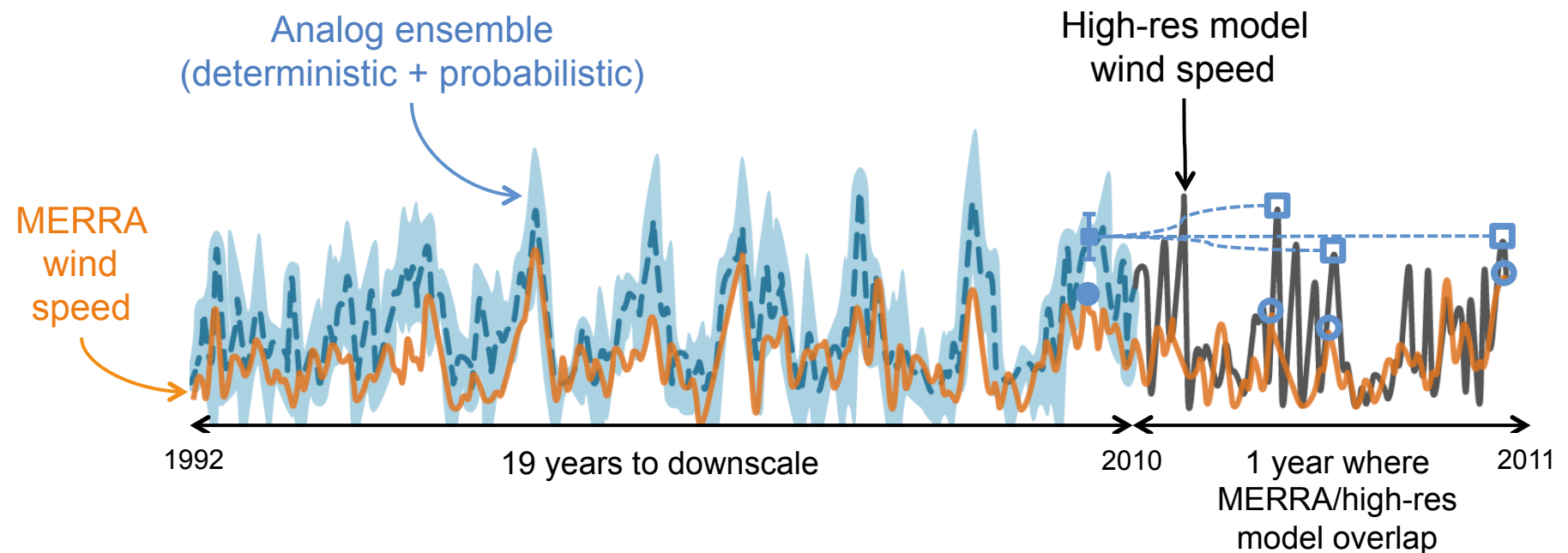
Training period: last 365 days, period downscaled: last 3 entire years, analogs: 25

AnEn for wind resource assessment in areas with no observations



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- Recreate a long-term observation-based wind climatology at site
- Downscale a long-term NASA Modern-Era Retrospective Analysis for Research and Applications (MERRA) time series using a short-term record from high-res model



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Summary and future work



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- The analog ensemble provides accurate predictions/estimates and reliable uncertainty quantification (at a lower computational cost) for
 - Short-term (0-48 h) weather predictions
 - Short-term (0-72 h) power predictions
 - Long-term wind resource assessment
- The analog ensemble could also be used to drastically reduce the computational cost of dynamical downscaling (with the added value of uncertainty quantification)
- Could it be a game-changer for some of these applications?
- Current/Future work:
 - AnEn optimization (e.g., adaptive number of analogs)
 - Explore new predictors, and new predictor selection criteria
 - Tests with multi-year training data set

Thanks!

(lucadm@ucar.edu)

References:

- Delle Monache et al., 2011: Kalman filter and analog schemes to postprocess numerical weather predictions. *Monthly Weather Review*, **139**, 3554–3570.
- Delle Monache et al., 2013: Probabilistic weather predictions with an analog ensemble. Accepted to appear on *Monthly Weather Review*.
- Alessandrini, Delle Monache et al., 2013: Probabilistic power predictions with an analog ensemble. In preparation for *Applied Energy*.
- Nagarajan, Delle Monache et al., 2013: Performance of analog postprocessing methods across several variables and forecast models. In preparation for *Weather and Forecasting*.
- Vanvyve, Delle Monache et al., 2013: Wind resource assessment with an analog ensemble. In preparation for *Journal of Applied Meteorology*.



Estes Park, 2009

Research Applications Laboratory

Foote, Director

Mahoney, Deputy Director

Hoswell, Lab Administrator

**Administration
Systems Admin
Multi-media**

Staff are housed within the six Programs below, but work across projects in a matrix fashion

Aviation Appl. Program

Carmichael

Politovich/Barron

Hydromet Appl. Program

Rasmussen

Steiner/Blackburn

Wx Sys. & Assessment Prog.

Haupt

Drobot/Wiener

Nat'l DTC Director

Kuo

Nat'l Security Appl. Prog.

Swerdlin

Betancourt

Climate Sci. & Appl. Program

Buja

Miller

Joint Numerical Testbed

Brown

Nance/Carson

Projects

Icing
Ceiling and visibility
Dissemination of products
Storm prediction
Terrain-induced turbulence
Turbulence
Weather integration into decision making
Winter weather

Forecasting urban atmospheres
High performance computing for operational systems
Modeling hazardous plumes
Mesoscale current-climate downscaling
Operational NWP, improved data assimilation

Hydrometeorological modeling
Land-surface modeling
Precipitation and aerosols
Water and climate change
Short-term storm forecasting

GIS science program
Governance and adaptation
Resilient and sustainable cities
Regional adaptation to climate change
Weather, climate, and health

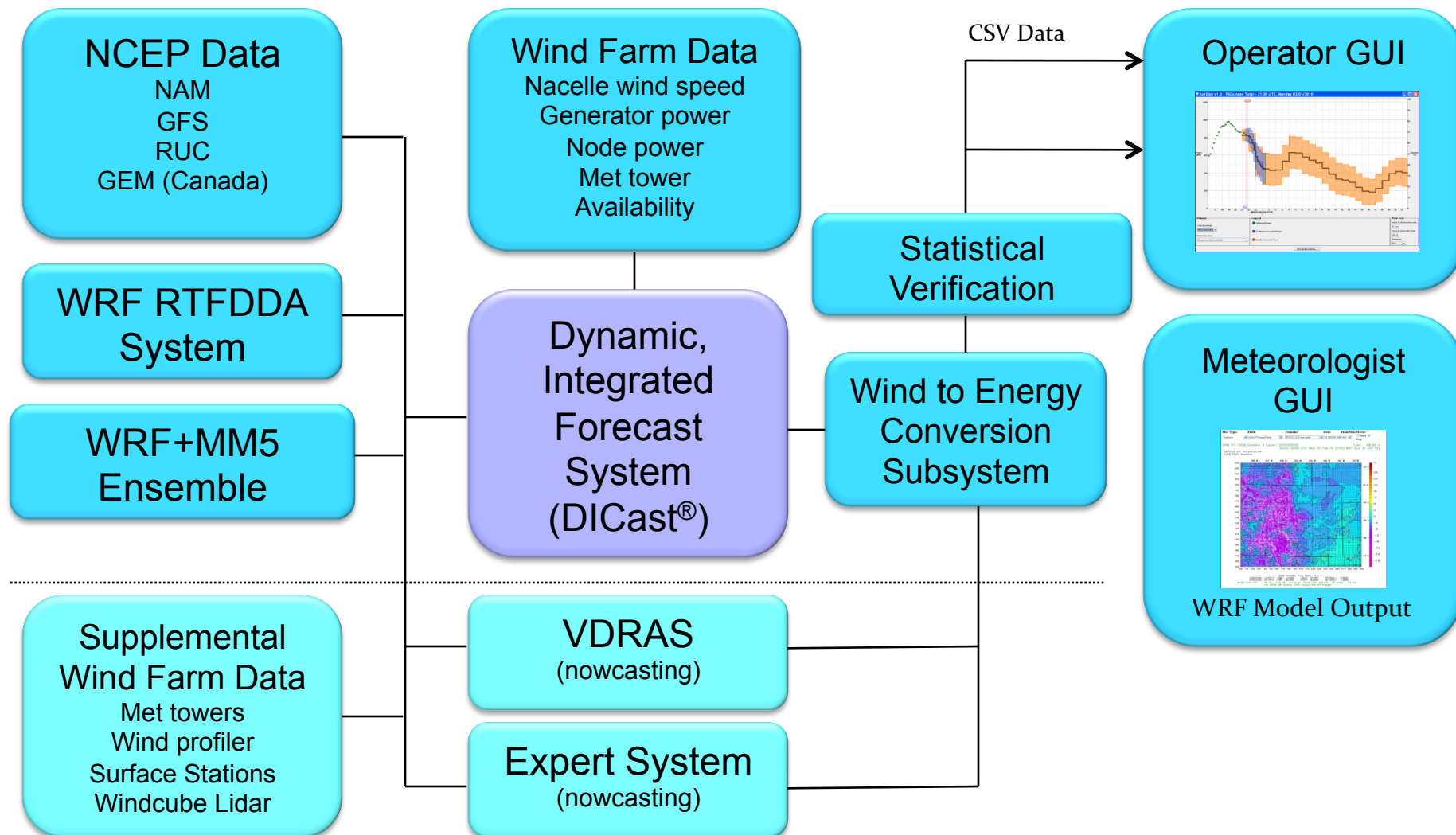
International aviation weather
Renewable energy
Statistical prediction systems
Surface transportation weather
Use and value of weather information

Advanced forecast evaluation methods
Data assimilation testing
Ensemble forecast evaluation
Hazardous weather and hydromet testbeds
Mesoscale model testing and evaluation
Tropical cyclone testbed

Project Managers control the project budgets



NCAR's Wind Energy Prediction System for Xcel Energy



NCAR-Xcel Energy Project

Accurate prediction economical benefits



NCAR

**~\$1.9M per each
percent
improvement**

2010 Total Benefit

- ▶ **Error Reduction (expected 2%)**
 - ▶ PSCo; NSP – much higher than expected
 - ▶ SPS – higher than expected
- ▶ **Rate of Savings**
 - ▶ PSCo – meets expectations (expected \$800k/%MAPE)
 - ▶ NSP – higher than expected (expected \$500k/%MAPE)
 - ▶ SPS – much lower than expected (expected 600k/%MAPE)

OpCo	2009	2010	Delta	Rate of Savings	Annualized
PSCo	18.07%	14.25%	-3.81%	\$ 850,665	\$ 3,245,102
NSP	15.66%	12.20%	-3.47%	\$ 748,827	\$ 2,596,873
SPS	16.26%	13.86%	-2.39%	\$ 175,000	\$ 418,443

*Mean Absolute Percent Error

Wind Forecasting Savings **\$ 6,260,417**

Curtailment Auditing Savings **\$ 1,260,000**

Grand Total **\$ 7,520,417**



NCAR-Xcel Energy Project

CO₂ reduction due to accurate predictions



NCAR

“The avoided generation occurred when Xcel cycled offline baseload thermal units (coal or natural gas combined cycle) due to extended periods of forecasted low loads and high winds.”

AVOIDED EMISSIONS DUE TO IMPROVED PREDICTIONS: 238,136 TONS OF CO₂

MWh's of avoided generation in 2011

Arapahoe 3 = 317
Arapahoe 4 = 6,941
Cherokee 1 = 11,606
Cherokee 2 = 13,772
Valmont 5 = 10,061
FSV CC = 93,626
RMEC CC = 308,989

Probabilistic forecast attributes: Economic value (value score)

Potential value of a forecast in a decision making framework; it can be estimated using a static cost-loss decision model for a dichotomous event (Wilks, 2006).

A decision maker can choose to pay a cost C (e.g., cost of evacuation efforts) to protect against a possible loss L (with $L > C$): if protective action is not taken, then the decision maker incurs a loss L if the adverse event occurs (e.g., lost lives).

Analysis of Value

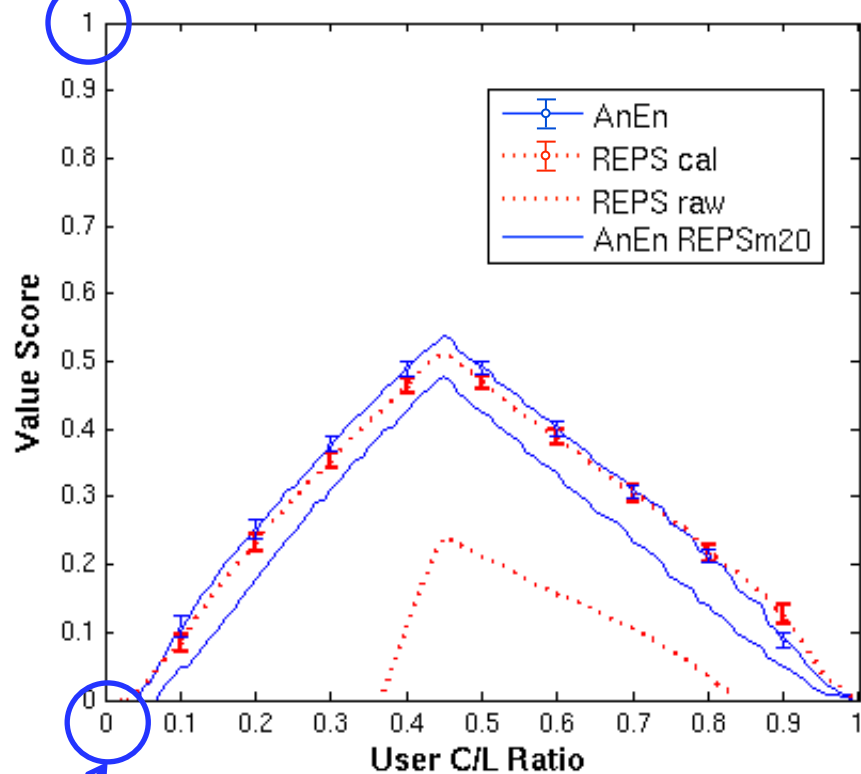


NCAR

Economic value diagram, 10-m wind speed ≥ 5 m/s

perfect forecast

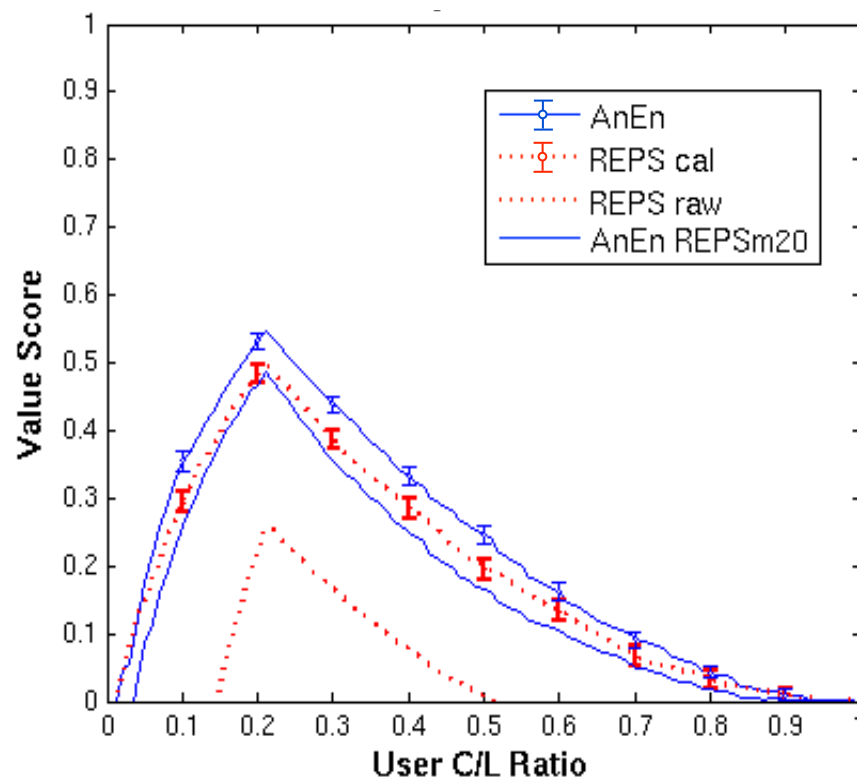
9-h Forecast



low risk

high risk

42-h Forecast

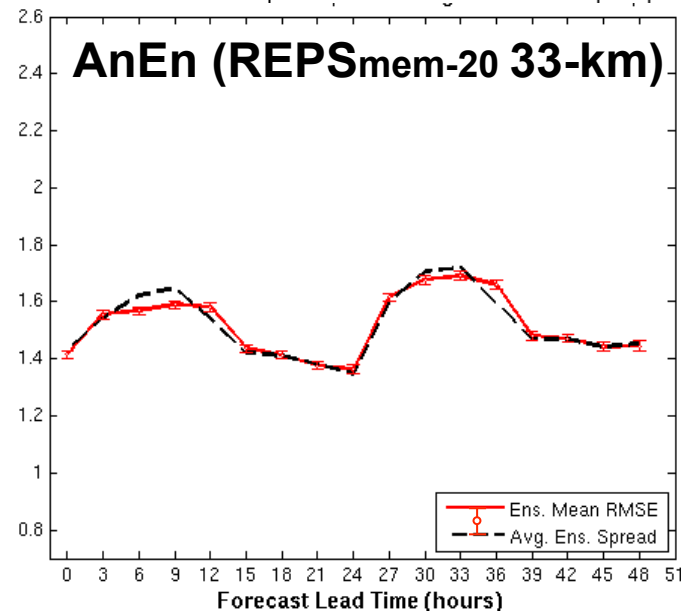
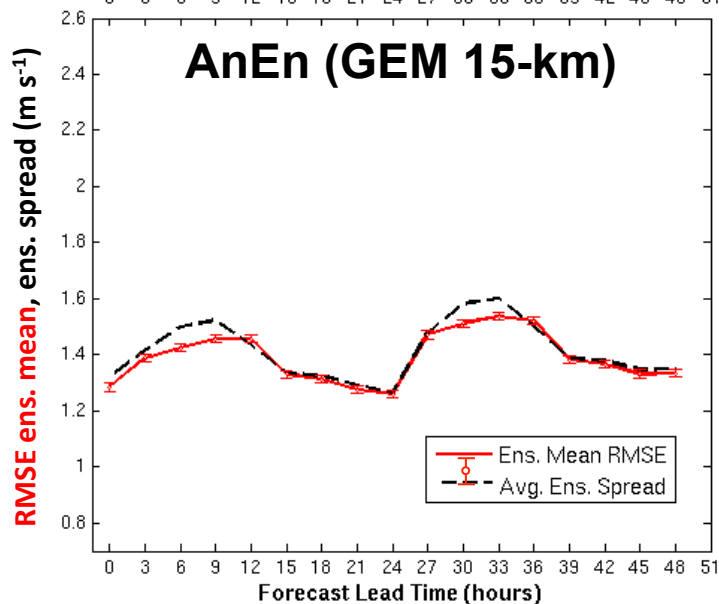
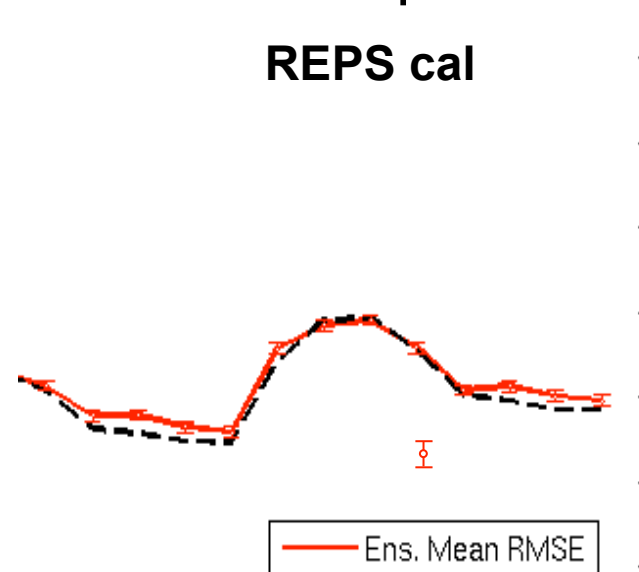
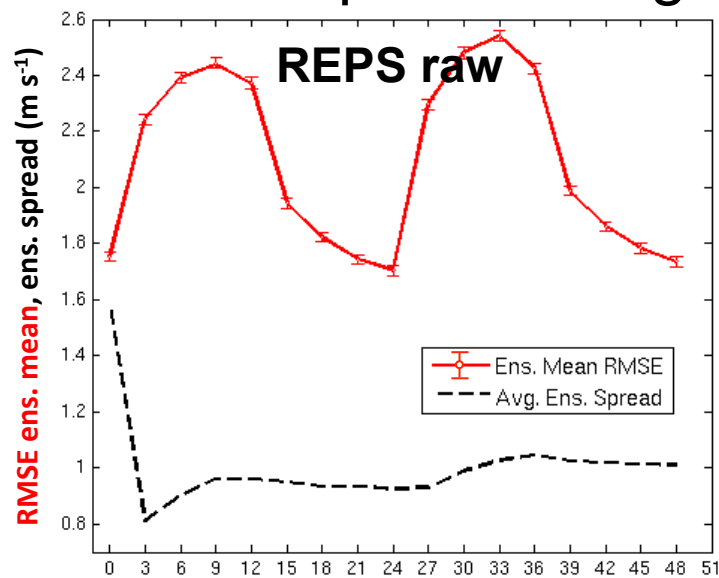


Analysis of spread-error consistency (1)



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Dispersion diagram for 10-m wind speed



Measuring Value



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Value Score (or *expense skill score*)

$$VS = \frac{E_{fcst} - E_{clim}}{E_{perf} - E_{clim}}$$

E_{fcst} = Expense from follow *the* forecast

E_{clim} = Expense from follow a climatological forecast

E_{perf} = Expense from follow a perfect forecast

$$VS = \frac{\frac{1}{M}(a\alpha + b\alpha + c) - \min(\alpha, \bar{o})}{\bar{o}\alpha - \min(\alpha, \bar{o})}$$

a = # of hits

b = # of false alarms

c = # of misses

d = # of correct rejections

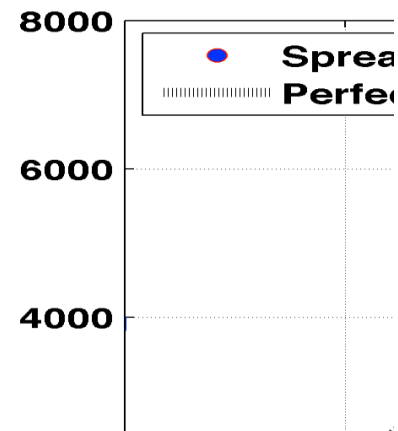
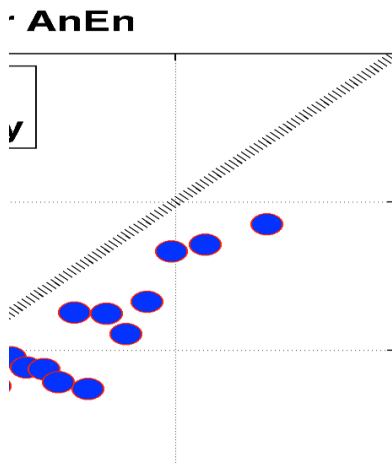
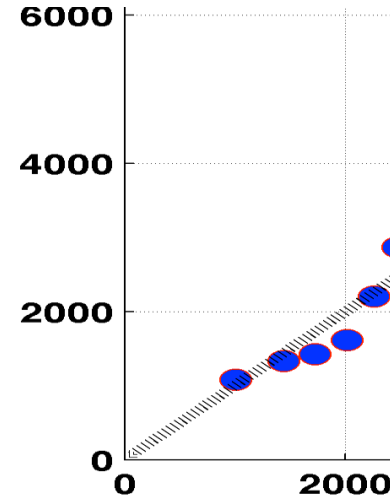
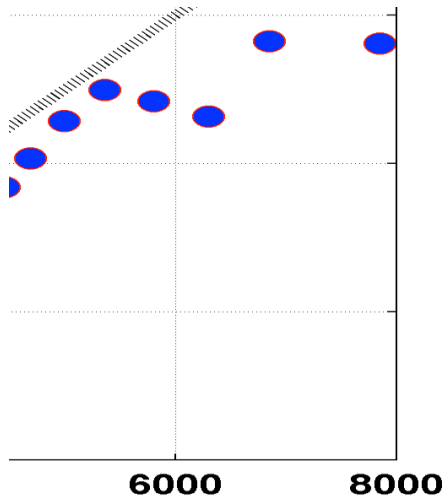
α = C/L ratio

$\bar{o} = (a+c) / (a+b+c+d)$

		Event Observed	
		Yes	No
Forecast and/or Prepare	Yes	a	b
	No	c	d

Power predictions (2)

Binned spread-skill diagram, power forecasts



The metric (1)

Analog strength for a particular forecast lead time t is measured by the distance between current and past forecast, over a short window, $2\tilde{t}$ wide

$$\|f_t - g_{t'}\| = \frac{1}{\sigma_f} \sqrt{\sum_{k=-\tilde{t}}^{+\tilde{t}} (f_{t+k} - g_{t'+k})^2}$$

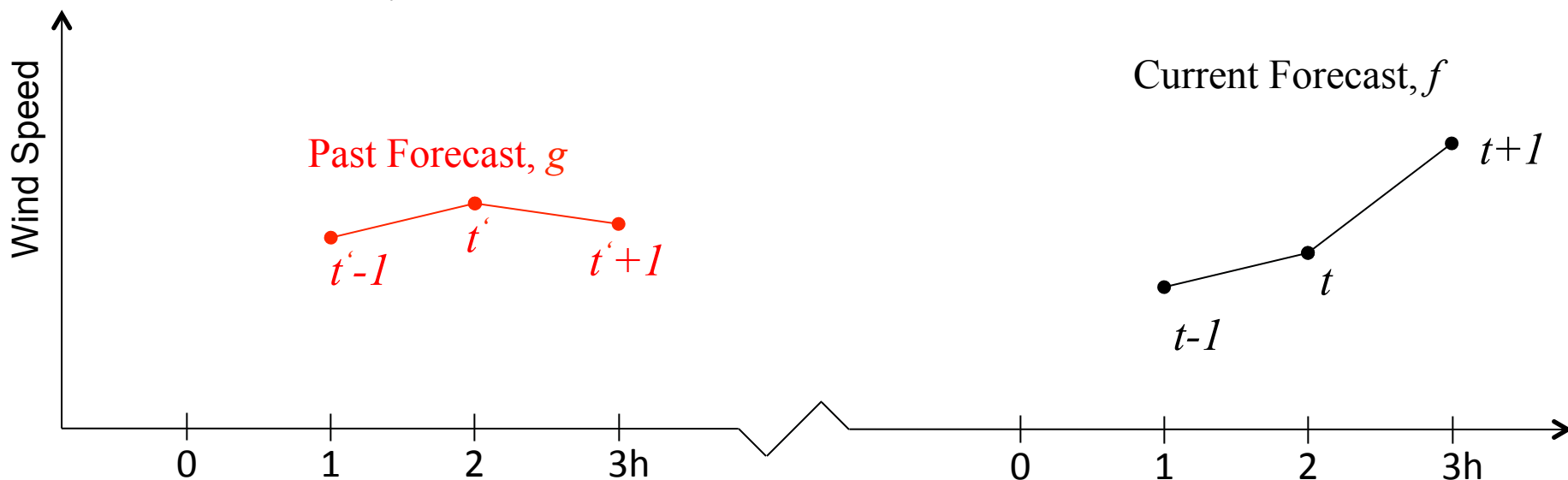
σ_f : Forecasts' standard deviation over entire analog training period

Expanded to multiple predictor variables, but still focused on predictand f :
(for wind speed, predictors are speed, direction, sfc. temp., sfp pressure, and PBL depth)

$$\|f_t - g_{t'}\| = \sum_{v=1}^{N_v} \frac{w_v}{\sigma_{f^v}} \sqrt{\sum_{k=-\tilde{t}}^{+\tilde{t}} (f_{t+k}^v - g_{t'+k}^v)^2}$$

N_v : Number of predictor variables

w_v : Weight given to each predictor

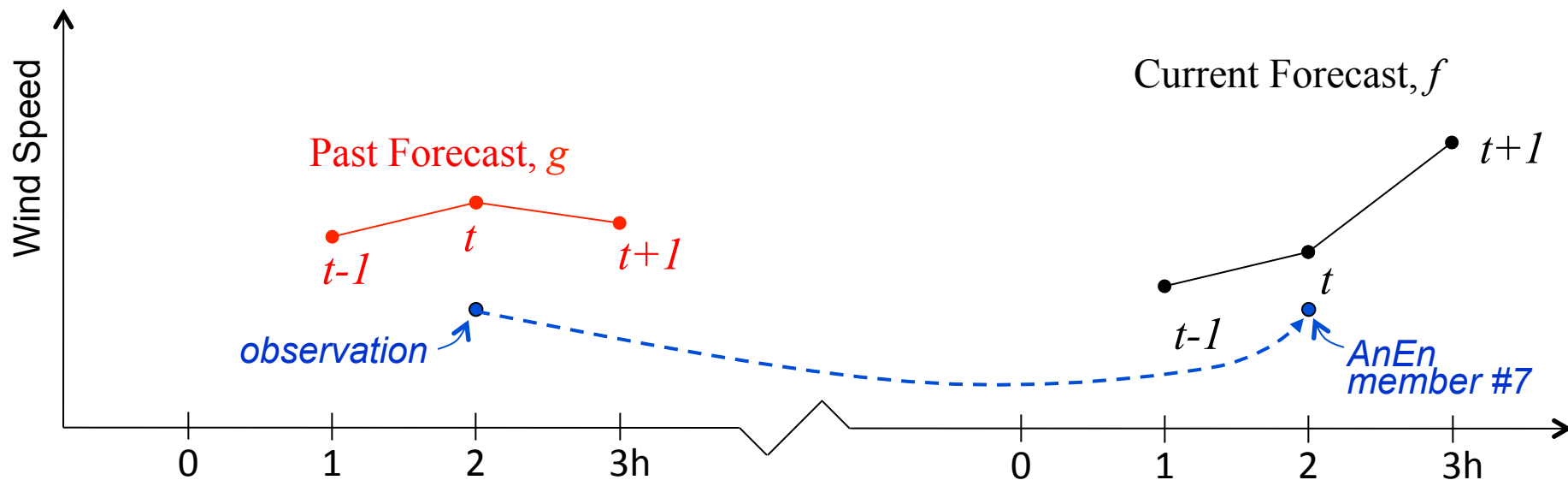


The metric (2)



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After finding the n strongest analogs, each of the n AnEn members is taken as the verifying observation from each analog.

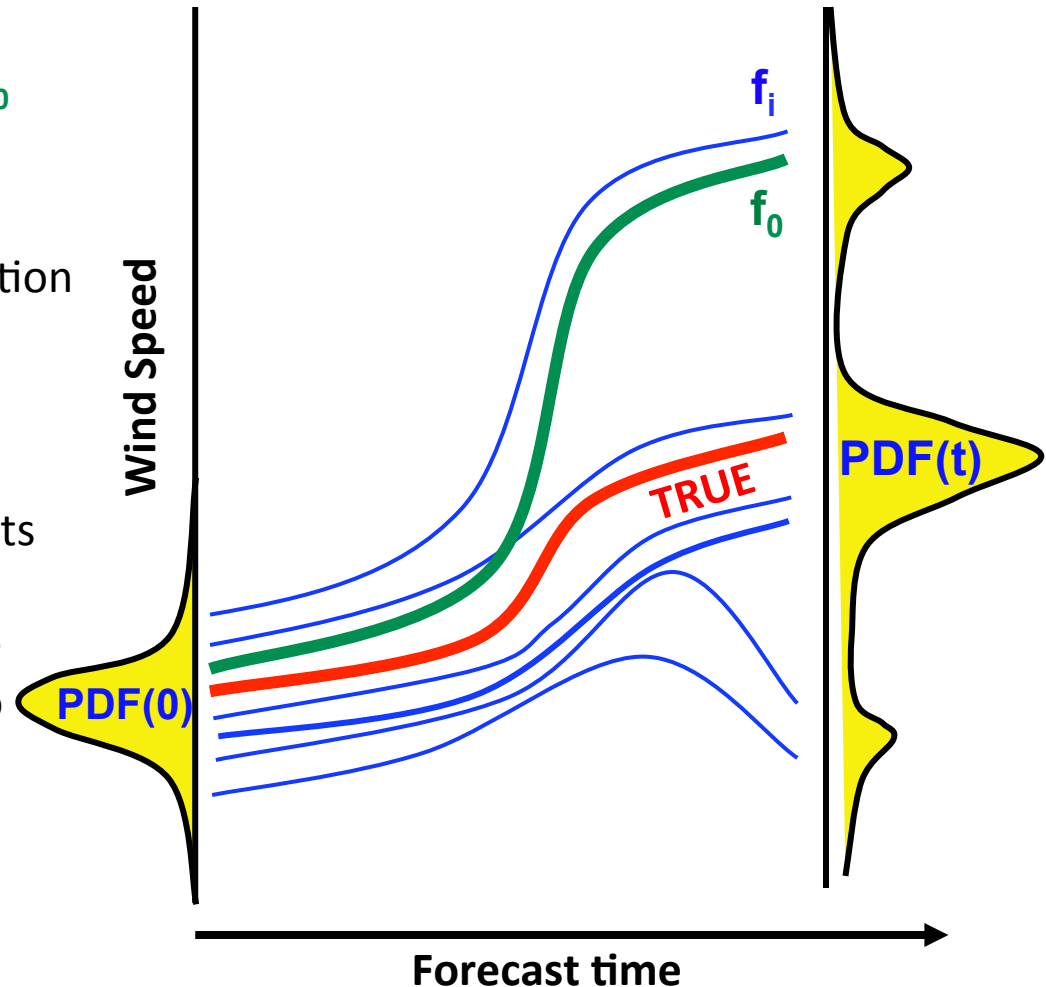


Ensemble Prediction

The single deterministic forecast f_0 fails to predict the **TRUE**

The initial probability density function **PDF(0)** represents the initial uncertainties

An ensemble of perturbed forecasts f_i , starting from perturbed initial conditions designed to sample the initial uncertainties can be used to estimate the probability of future states **PDF(t)**



Cost-benefit of the analog technique (1)

- Design, implementation, and maintenance of the analog and NWP ensemble techniques
 - Shared requirements
 - NWP-model-based data assimilation and forecast.
 - Calibration: both approaches use a calibration technique, and each requires about the same effort to develop and implement
 - Unique requirements for REPS
 - Multiple physics packages (for multimodel ensembles), and
 - Stochastic physics routines

Cost-benefit of the analog technique (2)

- Computational expense

- SCENARIO I: You must run your own NWP model
 - REPS requires about 2-3 times more calculations than the analog technique
- SCENARIO II: Use an available NWP product (e.g., from NCEP)
 - REPS requires orders of magnitude more calculations than the analog technique

NASA's MERRA

• Introduction

NCAR

- NASA Modern-Era Retrospective Analysis for Research and Applications (MERRA)

Based on NASA's Global Atmospheric Model and Data Assimilation System

3-D worldwide record of weather from 1979

1/2 degrees latitude \times 2/3 degrees longitude

Hourly surface 2D and 6 hourly 3D fields

Assimilation of all NASA historical satellite data

Conventional data

